

Efficient Time Series Clustering from Multiscale Reservoir Dynamics with Granular-Ball Anchoring Graph Optimization

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Abstract

Time-series clustering remains challenging due to the inherent trade-off between clustering effectiveness and computational efficiency. Similarity-based methods often suffer from quadratic complexity caused by pairwise distance computations, while deep learning-based approaches typically rely on costly iterative training and a large number of trainable parameters. In this paper, we propose MSRGC-Net, an efficient time-series clustering framework that integrates multiscale reservoir computing, granular-ball-based anchoring graph construction, and consensus learning. MSRGC-Net adopts a training-free reservoir computing paradigm to extract multiscale temporal representations from raw time series without backpropagation, significantly reducing computational overhead. To capture the intrinsic structure of the resulting representations, granular-ball computing is employed to adaptively model data distributions via density-consistent regions, yielding compact and robust anchor graph representations. Furthermore, a consensus-based anchoring graph optimization strategy is introduced to effectively align multiscale reservoir representations and integrate complementary information across temporal scales. Extensive experiments on widely used univariate and multivariate benchmark datasets demonstrate that MSRGC-Net consistently outperforms state-of-the-art methods in clustering performance while maintaining superior computational efficiency.

1 Introduction

Massive time-series data are ubiquitous in both scientific research and real-world applications, including health monitoring [Mikalsen *et al.*, 2016], human activity recognition [Ma *et al.*, 2017], speech analysis [Trentin *et al.*, 2015] and environmental science [Hipel and McLeod, 1994]. As a fundamental unsupervised learning task, time-series clustering aims to dis-

cover intrinsic temporal structures from unlabeled sequential data and plays a crucial role in large-scale data analysis.

Early time-series clustering methods typically combine classical clustering algorithms, such as k-means [Petitjean *et al.*, 2011] and k-Shape [Paparrizos and Gravano, 2015], with distance measures defined directly on raw time series, including Euclidean distance [Yang and Leskovec, 2011] and Dynamic Time Warping (DTW) [Cuturi and Blondel, 2017]. Although conceptually simple, these distance-based approaches suffer from two well-known limitations: they are sensitive to noise and complex temporal variations, and they incur quadratic computational complexity due to repeated pairwise distance calculations, which severely limits their scalability.

To alleviate these issues, feature-based clustering methods [Guo *et al.*, 2008] first transform time series into compact representations before clustering. While improving efficiency and robustness, their performance strongly depends on handcrafted features and domain expertise, and important temporal information may be lost during feature extraction. Moreover, deep learning-based approaches [Madiraju, 2018; Ma *et al.*, 2019] have demonstrated powerful representation learning capability. However, their reliance on iterative training, extensive hyperparameter tuning, and large computational budgets poses significant challenges for large-scale and resource-constrained time-series clustering scenarios.

These limitations highlight a fundamental challenge in time-series clustering: *how to learn expressive temporal representations while maintaining high computational efficiency*. Addressing this challenge requires rethinking both representation learning and clustering strategies. In particular, two key issues remain largely unresolved.

First, temporal representations learned under different model configurations or scales often capture complementary dynamic characteristics. Although exploiting such diversity is beneficial for clustering, existing methods typically rely on repeated training or complex ensembles, leading to substantial computational overhead. How can multiscale and diverse representations be generated efficiently without costly training procedures?

Second, most existing methods apply k-means-based or spectral clustering directly to learned representations, which assume simple cluster geometries and scale poorly with

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dataset size. How can clustering be redesigned to improve robustness and scalability while avoiding expensive point-wise affinity modeling?

In this paper, we propose **MSRGC-Net** (**M**ulti-**S**cale **R**eservoir **G**ranular-ball **C**onsensus **N**etwork), an efficient time-series clustering framework that integrates multi-scale reservoir computing, granular-ball-based anchoring graph construction, and consensus learning to address these challenges. MSRGC-Net adopts a training-free reservoir computing paradigm to extract multiscale temporal representations using a set of fixed reservoirs with different spectral radii, enabling efficient representation learning without backpropagation. To capture the intrinsic structure of the resulting reservoir representations, granular-ball computing is employed to model data distributions via compact, density-consistent regions, yielding a set of representative anchors. Furthermore, a consensus-based anchoring graph optimization strategy is introduced to align and integrate multiscale reservoir representations within a unified clustering framework. By combining training-free multiscale encoding, region-level abstraction, and anchor-based consensus graph modeling, MSRGC-Net effectively balances representation expressiveness and computational efficiency, making it well suited for large-scale time-series clustering.

Main contributions are summarized as follows

- i) We propose a training-free multiscale reservoir encoding mechanism that captures complementary temporal dynamics with different spectral radii.
- ii) We introduce a granular-ball-based anchoring representation that compactly models the reservoir state distributions and enables efficient clustering.
- iii) We formulate time-series clustering as a consensus-based anchoring graph optimization problem, providing a unified and lightweight framework for integrating multiscale dynamics.

2 Related Work

2.1 Time-Series Clustering

Time-series clustering aims to group unlabeled time series by exploiting their intrinsic dynamics. Early methods are mainly relying on similarity measures defined directly on time series, such as DTW-based clustering [Cuturi and Blondel, 2017] and k-Shape [Paparrizos and Gravano, 2015]. Although effective in capturing local temporal patterns, these approaches require pairwise distance computations and thus suffer from quadratic complexity, limiting their scalability.

To improve efficiency, representation-based methods adopt a “transform-then-cluster” paradigm. Representative approaches include statistical feature extraction [Guijo-Rubio *et al.*, 2020], kernel-based models such as TCK [Mikalsen *et al.*, 2018], and feature fusion frameworks like Time2Feat [Bonifati *et al.*, 2022]. While reducing computational cost, these methods rely on handcrafted or predefined representations and may fail to capture complex nonlinear dynamics.

More recently, deep learning-based methods learn data-adaptive temporal representations, including autoencoder-based approaches [Ma *et al.*, 2019; Yang and Lin, 2024] and joint learning frameworks [Madiraju, 2018; Meng *et al.*,

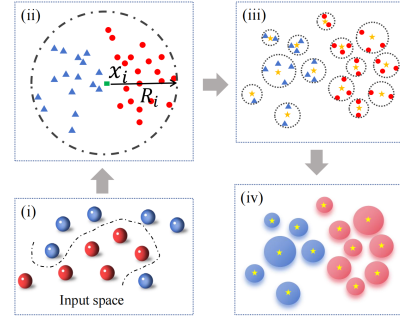


Figure 1: Example of using granular balls for anchoring.

2023]. Despite their strong expressive power, these methods require iterative training with many parameters, resulting in high computational cost and limited scalability. In contrast, our work achieves expressive temporal representations without iterative network training by exploiting the intrinsic dynamics of reservoir computing and coupling them with a lightweight clustering optimization strategy.

2.2 Reservoir Computing for Time-Series

Reservoir computing (RC), particularly Echo State Networks (ESNs) [Jaeger, 2001], provides an efficient framework for temporal modeling by employing fixed recurrent dynamics and avoiding backpropagation. Owing to its training-free nature, RC has been widely applied to time-series forecasting, classification, and anomaly detection [Bianchi *et al.*, 2015; Ullah *et al.*, 2022]. To enhance representation capacity, deep and multi-reservoir ESN architectures have been explored to capture temporal dynamics at multiple scales [Ma *et al.*, 2020]. However, existing reservoir-based methods are mainly designed for supervised tasks, and unsupervised approaches typically rely on a single reservoir and apply conventional clustering directly to reservoir states, limiting their ability to exploit complementary multiscale dynamics.

2.3 Multi-View Graph Clustering

Multi-view graph clustering [Zhan *et al.*, 2017; Li *et al.*, 2020] is an important branch of multi-view clustering [Gao *et al.*, 2023]. Our work is also inspired by multi-view graph clustering, which fuses complementary representations via graph-based optimization. Although anchor-based methods [Wang *et al.*, 2022] improve scalability, their extension to time-series data remains limited due to the difficulty of capturing multiscale temporal representations.

Granular-ball computing (GBC) [Xia *et al.*, 2019] provides a density-aware, region-level abstraction that enables each anchor to represent a compact local region rather than an isolated data point, as illustrated in Figure 1. By operating at the regional level, GBC captures intrinsic local structures and bridges fine-grained instance-level information with higher-level semantic organization—an effect that is difficult to achieve using purely point-based representations [Xia *et al.*, 2025b; Wang *et al.*, 2026b; Xia *et al.*, 2022]. Such region-based modeling is particularly beneficial for multiscale reservoir representations [Shen *et al.*, 2026; Xia *et al.*, 2025a], where structural patterns are distributed

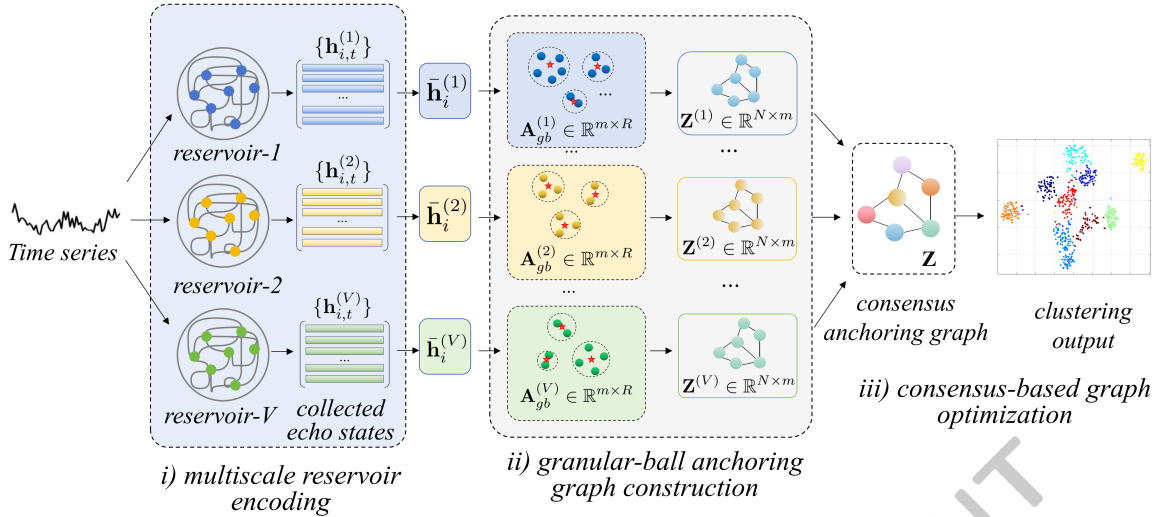


Figure 2: Illustration of the proposed MSRGC-Net.

across different temporal resolutions. Motivated by this observation, we incorporate granular-ball-based anchoring into a consensus-based multi-view graph optimization framework, enabling scalable and structure-aware time-series clustering.

3 Methodology

In this section, we formally elaborate on the proposed MSRGC-Net (Multi-Scale Reservoir Granular-ball Consensus Network), a multiscale reservoir network with granular-ball-based anchoring graph optimization for efficient time-series clustering.

As illustrated in Figure 2, MSRGC-Net consists of three main stages: i) multiscale reservoir encoding, which extracts training-free temporal representations from raw time series; ii) granular-ball anchoring graph construction, which builds a structured and compact graph representation to capture the intrinsic data organization; and iii) consensus-based graph optimization for clustering, which integrates multi-scale reservoir representations through lightweight optimization.

3.1 Multi-Scale Reservoir Encoding

Echo State Networks (ESNs) are a representative realization of reservoir computing, where a fixed recurrent neural network projects low-dimensional input sequences into a high-dimensional dynamical state space. Given a multivariate time series dataset $\mathcal{X} = \{\mathbf{x}_i\}_{i=1}^N$ ($\mathbf{x}_i \in \mathbb{R}^{T \times D}$), the reservoir state of the i -th sample at time step t , denoted by $\mathbf{h}_{i,t} \in \mathbb{R}^R$, is obtained by the following update equation:

$$\mathbf{h}_{i,t} = \tanh(\mathbf{W}_{\text{in}}\mathbf{x}_{i,t} + \mathbf{W}_{\text{r}}\mathbf{h}_{i,t-1}), \quad (1)$$

where $\mathbf{W}_{\text{in}} \in \mathbb{R}^{R \times D}$ and $\mathbf{W}_{\text{r}} \in \mathbb{R}^{R \times R}$ are the input and recurrent weight matrices, and R is the number of reservoir units. In practice, $\mathbf{h}_i(0)$ can be initialized as a zero vector (or a small random vector), and the nonlinear activation $\tanh(\cdot)$ provides a bounded and smooth state transition to capture nonlinear temporal dependencies. These weights are randomly initialized and kept fixed during learning, enabling

efficient and stable extraction of temporal dynamics without backpropagation.

A single ESN configuration is generally inadequate for modeling the diverse temporal dependencies exhibited by complex time series. The dynamical behavior and memory capacity of an ESN are largely determined by the spectral radius ρ of the recurrent weight matrix $\mathbf{W}_{\text{r}}$. Specifically, smaller values of ρ favor short-term transient dynamics, whereas values approaching unity drive the reservoir toward the “edge of chaos,” enabling the preservation of long-term temporal dependencies [Ma *et al.*, 2020]. Motivated by this observation, we construct V independent reservoirs with distinct spectral radii $\mathcal{P} = \{\rho_1, \dots, \rho_V\}$ to capture complementary temporal patterns at multiple scales, thereby forming a set of multi-scale reservoir views.

For the i -th time series processed by the v -th reservoir, a sequence of reservoir states $\{\mathbf{h}_{i,t}^{(v)}\}_{t=1}^T$ is generated according to Equation (1). To obtain a compact view-specific representation, temporal aggregation is applied to the reservoir states, yielding

$$\bar{\mathbf{h}}_i^{(v)} = \frac{1}{T} \sum_{t=1}^T \mathbf{h}_{i,t}^{(v)} \in \mathbb{R}^R. \quad (2)$$

By stacking the aggregated representations of all N samples, we form the view-specific feature matrix $\mathbf{H}^{(v)} = [\bar{\mathbf{h}}_1^{(v)}, \bar{\mathbf{h}}_2^{(v)}, \dots, \bar{\mathbf{h}}_N^{(v)}]^\top \in \mathbb{R}^{N \times R}$, which is subsequently used as the input to the granular-ball anchoring graph construction.

3.2 Granular-Ball Anchoring Graph

Given multi-scale reservoir representations $\{\mathbf{H}^{(v)}\}_{v=1}^V$, directly constructing a consensus graph over all samples is computationally prohibitive. To enable scalable modeling while preserving the intrinsic structure of the data, we construct a granular-ball anchoring graph based on granular-ball computing (GBC) [Xia *et al.*, 2019]. Specifically, GBC transforms each view-specific feature matrix $\mathbf{H}^{(v)}$ into a compact set of representative anchors, which serve as structural

proxies of the original data distribution [Jiang *et al.*, 2025] and form the basis of an anchor-based graph representation [Cheng *et al.*, 2023].

Intuitively, granular-ball computing can be regarded as a region-inducing operator that groups point-wise representations into adaptive local regions, thereby capturing density and geometric structure beyond individual samples. Given $\mathbf{H}^{(v)}$, the operator iteratively partitions the feature space and outputs a collection of granular regions, referred to as granular balls. This design is inspired by the global-priority principle in cognitive computing and the multi-granularity learning framework. Below, we introduce the key components of the granular-ball anchoring graph construction.

Definition 1. Granular Ball. Given the representations $\mathbf{H}^{(v)}$ of all samples, granular-ball computing produces a set of granular balls $\mathbf{GB} = \{GB_k\}_{k=1}^M$. Each granular ball GB_k is characterized by a center $\mathbf{c}_k$ and a radius r_k , defined as

$$\mathbf{c}_k = \frac{1}{|GB_k|} \sum_{\bar{\mathbf{h}}_{i_k} \in GB_k} \bar{\mathbf{h}}_{i_k}, \quad (3)$$

$$r_k = \max_{\bar{\mathbf{h}}_{i_k} \in GB_k} \|\bar{\mathbf{h}}_{i_k} - \mathbf{c}_k\|_2. \quad (4)$$

Definition 2. Quality of Granular Ball. The structural quality of a granular ball GB_k is measured by the distribution measure (DM) [Xie *et al.*, 2024], defined as

$$DM(GB_k) = \frac{1}{|GB_k|} \sum_{\bar{\mathbf{h}}_{i_k} \in GB_k} \|\bar{\mathbf{h}}_{i_k} - \mathbf{c}_k\|_2, \quad (5)$$

where a smaller DM value indicates a more compact and homogeneous region.

Definition 3. Granular-Ball Splitting Criterion. To adaptively refine granular regions, each granular ball GB is tentatively split into two sub-balls GB_1 and GB_2 using 2-means clustering. The split is accepted if the following weighted criterion is satisfied:

$$DM_w = \frac{|GB_1|}{|GB|} DM(GB_1) + \frac{|GB_2|}{|GB|} DM(GB_2). \quad (6)$$

If $DM_w < DM(GB)$, the split is retained; otherwise, the splitting process terminates. This procedure is repeated until no further quality-improving splits are possible.

Applying the granular-ball operator yields M granular balls, where M controls the granularity of the induced regions and balances structural fidelity with computational efficiency. To construct a compact anchoring graph, we select the top m core granular-ball anchors ($m < M < N$). Anchor selection is guided by the following score:

$$\text{score}(GB_i) = DM(GB_i) \cdot \min_{j \in \mathcal{S}_{q-1}} \|\mathbf{c}_i - \mathbf{c}_j\|_2, \quad (7)$$

where $\mathcal{S}_{q-1}$ denotes the set of previously selected anchors. This criterion jointly accounts for regional compactness and spatial diversity, enabling the selected anchors to preserve the skeletal structure of the data distribution.

Given m granular-ball anchors for each view, denoted as $\{\mathbf{A}_{gb}^{(v)} \in \mathbb{R}^{m \times R}\}_{v=1}^V$, where each anchor corresponds to the

center of a selected granular ball, we construct a view-specific granular-ball anchoring graph $\mathbf{Z} \in \mathbb{R}^{N \times m}$ to obtain a sample-to-anchor representation [Liu *et al.*, 2026]. Unlike conventional point-to-point affinity graphs, this anchoring graph models relationships between samples and density-consistent granular-ball anchors, whose centers summarize local data regions and capture intrinsic structural patterns while suppressing the influence of local noise. By replacing sample-level interactions with anchor-level connections, the proposed representation significantly reduces memory and computational complexity, while providing a robust and structurally faithful foundation for subsequent consensus learning.

3.3 Consensus Anchoring Graph Learning

Based on $\{\mathbf{Z}^{(v)}\}_{v=1}^V$ the view-specific granular-ball anchoring graphs constructed in the previous step, we further learn a unified consensus representation $\mathbf{Z}$ that integrates complementary information from multiple views. To jointly model view-wise data reconstruction, cross-view alignment, and global structural regularization, we formulate the following unified optimization problem:

$$\begin{aligned} \min_{\mathbf{Z}, \{\mathbf{Z}^{(v)}\}, \{\alpha^{(v)}\}} & \sum_{v=1}^V \left\| \mathbf{H}^{(v)} - \mathbf{Z}^{(v)} \mathbf{A}_{gb}^{(v)} \right\|_F^2 \\ & + \gamma \sum_{v=1}^V (\alpha^{(v)})^r \left\| \mathbf{Z} - \mathbf{Z}^{(v)} \right\|_F^2 + \lambda \|\mathbf{Z}\|_F^2 \\ \text{s.t. } & \mathbf{Z} \geq 0, \mathbf{Z}^{(v)} \geq 0, \mathbf{Z}\mathbf{1} = \mathbf{1}, \mathbf{Z}^{(v)}\mathbf{1} = \mathbf{1}, \end{aligned} \quad (8)$$

where $\mathbf{Z}^{(v)} \in \mathbb{R}^{N \times m}$ denotes the view-specific sample-to-anchor assignment matrix, and $\mathbf{Z} \in \mathbb{R}^{N \times m}$ represents the global consensus anchoring graph. Intuitively, the first term enforces faithful reconstruction of view-specific reservoir representations using granular-ball anchors. The second term encourages consistency between each view-specific anchoring graph and the global consensus graph, while the third term imposes global regularization to improve robustness and prevent overfitting. The adaptive weights $\{\alpha^{(v)}\}_{v=1}^V$ automatically adjust the contribution of each view according to its alignment quality with the consensus representation. Following [Chen *et al.*, 2023], we set $r = 2$ to ensure stable weight smoothing and convergence behavior. The parameters γ and λ control the strength of cross-view consistency and global regularization, respectively. Note that the objective function in Equation (8) is not jointly convex with respect to all variables. We therefore adopt an alternating optimization strategy, iteratively updating one variable while fixing the others until convergence.

Update of $\mathbf{Z}^{(v)}$. Fixing $\mathbf{Z}$ and $\{\alpha^{(v)}\}$, the subproblem with respect to $\mathbf{Z}^{(v)}$ reduces to a regularized least-squares problem. Its closed-form solution is given by

$$\mathbf{Z}^{(v)} = \left(\mathbf{H}^{(v)} \mathbf{A}_{gb}^{(v)\top} + \gamma (\alpha^{(v)})^r \mathbf{Z} \right) \left(\mathbf{A}_{gb}^{(v)} \mathbf{A}_{gb}^{(v)\top} + \gamma (\alpha^{(v)})^r \mathbf{I} \right)^{-1}. \quad (9)$$

Negative entries are truncated to zero to satisfy the non-negativity constraint.

Update of $\mathbf{Z}$. Fixing $\{\mathbf{Z}^{(v)}\}$ and $\{\alpha^{(v)}\}$, global consensus anchoring graph admits the closed-form update

$$\mathbf{Z} = \frac{\gamma \sum_{v=1}^V (\alpha^{(v)})^r \mathbf{Z}^{(v)}}{\gamma \sum_{v=1}^V (\alpha^{(v)})^r + \lambda}, \quad (10)$$

which corresponds to a weighted aggregation of view-specific anchoring graphs, with adaptive emphasis on more consistent views.

Update of α . Fixing $\mathbf{Z}$ and $\{\mathbf{Z}^{(v)}\}$, the adaptive view weights are updated via the Lagrange multiplier method as

$$\alpha^{(v)} = \frac{(q^{(v)})^{\frac{1}{1-r}}}{\sum_{v=1}^V (q^{(v)})^{\frac{1}{1-r}}}, \quad (11)$$

where $q^{(v)} = \gamma \|\mathbf{Z} - \mathbf{Z}^{(v)}\|_F^2$ measures the alignment error of the v -th view with respect to the consensus graph. Views with smaller alignment errors are thus assigned larger weights.

After convergence, the learned consensus anchoring graph $\mathbf{Z} \in \mathbb{R}^{N \times m}$ serves as a low-rank affinity representation of our MSRGC-Net. Final cluster assignments are obtained via spectral clustering by performing singular value decomposition:

$$\mathbf{Z} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^\top, \quad (12)$$

where $\mathbf{U} \in \mathbb{R}^{N \times k}$ contains the top- k left singular vectors. The final labels are produced by applying k -means to the rows of $\mathbf{U}$.

3.4 Complexity Analysis

The computational complexity of MSRGC-Net follows its three-stage framework. In the multiscale reservoir encoding stage, V training-free reservoirs perform forward propagation over T time steps, resulting in a complexity of $\mathcal{O}(VNTR^2)$, where R denotes the reservoir size. In the granular-ball anchoring graph construction stage, m representative anchors are generated with approximately linear complexity $\mathcal{O}(NR)$. In the consensus-based graph optimization stage, MSRGC-Net learns a sample-to-anchor graph $\mathbf{Z} \in \mathbb{R}^{N \times m}$, and the dominant cost comes from the spectral decomposition on $\mathbf{Z}$ with complexity $\mathcal{O}(Nm^2)$.

Since both the reservoir size R and the number of anchors m are typically fixed and satisfy $m \ll N$, MSRGC-Net achieves an overall near-linear complexity with respect to the number of samples N . Moreover, by integrating training-free reservoir computing and granular-ball region abstraction with an anchor-based consensus graph, MSRGC-Net avoids costly iterative optimization and point-wise affinity modeling, thereby offering a clear efficiency advantage over conventional quadratic graph-based clustering methods and deep models.

4 Experiments

Dataset. We evaluate the proposed MSRGC-Net on ten benchmark time-series datasets drawn from the UCR and UEA archives [Dau *et al.*, 2019; Bagnall *et al.*, 2018], covering a wide range of application domains, including human activity recognition, healthcare, industrial manufacturing, speech processing, etc. The datasets span diverse sequence lengths and dataset sizes.

Evaluation metrics. Clustering performance is evaluated using three standard metrics [Rand, 1971]: Normalized Mutual Information (NMI), Adjusted Rand Index (ARI), and Rand Index (RI). Together, these metrics provide complementary information-theoretic and pairwise-consistency evaluations.

Baselines. We compare MSRGC-Net with representative time-series clustering methods from three categories. (i) *Raw data-based methods* operate directly on the original time series, including k-Shape [Paparrizos and Gravano, 2015], Fuzzy-kShape [Fahiman *et al.*, 2017], and TCK [Mikalsen *et al.*, 2018]. (ii) *Representation learning-based methods* perform clustering in a learned feature space, covering both feature learning and deep clustering approaches, such as Modular-RC [Petitjean *et al.*, 2011], GRAIL [Paparrizos and Franklin, 2019], Time2Feat [Bonifati *et al.*, 2022], DEC [Xie *et al.*, 2016], TimeSURL [Liu and Chen, 2024], and TFMCC [Wang *et al.*, 2026a]. (iii) *Multi-view clustering methods* integrate information from multiple views, including GB-SMKKM [Xia *et al.*, 2025c] and MV-CAGAF [Wang *et al.*, 2025].

Implementation details. A common set of reservoir hyperparameters was used across all datasets, including reservoir size $R = 400$, connectivity $\beta = 0.25$, input scaling $\omega = 0.15$, noise level $\xi = 0.001$, number of views $V = 3$, and a spectral radius determined by a predefined strategy. For the consensus graph optimization, two regularization parameters were tuned from small candidate sets via grid search, with the multi-view alignment coefficient $\gamma = 10^3$ and the structural constraint parameter $\lambda = 10^{-1}$. All experiments were repeated ten times with random initializations and conducted on a 64-bit machine with an Intel i7-12700 CPU and 64 GB RAM.

4.1 Main Results

As shown in Table 1, MSRGC-Net achieves competitive and stable performance on multivariate time series clustering tasks, yielding favorable results compared with ten representative and state-of-the-art baseline methods across NMI, ARI, and RI. Across 5 multivariate datasets and 15 evaluation results, MSRGC-Net obtains the best performance on 12 metrics and ranks second on two metrics, indicating consistent behavior across different settings.

Improvements are more noticeable on datasets with higher channel dimensions and longer sequences, where modeling cross-variable temporal dependencies becomes increasingly important. For example, on the JapaneseVowels (JV) dataset, which involves variable-length and strongly coupled speech signals, MSRGC-Net achieves an ARI of 0.750, improving upon the second-best method GRAIL by 16.9%. On the Cricket (Cric) dataset with ultra-long time series ($T = 1197$), MSRGC-Net maintains strong performance across all three metrics, with an average score of 0.932. Similarly, on the CharacterTrajectories (CT) dataset containing 20 classes, MSRGC-Net attains the highest NMI of 0.789, markedly outperforming the single-view baseline rm-ESN (NMI = 0.476). Compared with raw data-based methods, MSRGC-Net leverages reservoir-based feature extraction to capture temporal dynamics across multiple variables. Relative to deep learning approaches, MSRGC-Net attains comparable or improved

Models	CT			JV			BM			Cric			SCP1		
	NMI	ARI	RI	NMI	ARI	RI	NMI	ARI	RI	NMI	ARI	RI	NMI	ARI	RI
TCK	0.589	0.158	0.811	0.446	0.268	0.676	<u>0.689</u>	0.603	0.841	0.812	0.647	0.947	0.141	0.198	0.621
	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.002)	(0.003)	(0.001)	(0.008)	(0.007)	(0.005)
K-shape	0.322	0.107	0.684	0.143	0.064	0.778	0.598	0.543	0.830	0.508	0.276	0.835	0.073	0.085	0.542
	(0.012)	(0.008)	(0.006)	(0.015)	(0.009)	(0.008)	(0.018)	(0.015)	(0.010)	(0.011)	(0.009)	(0.007)	(0.020)	(0.015)	(0.012)
Fc-shape	0.421	0.059	0.721	0.210	0.059	0.634	0.664	<u>0.607</u>	0.787	0.804	0.517	0.897	0.132	0.130	0.565
	(0.011)	(0.006)	(0.005)	(0.014)	(0.008)	(0.009)	(0.015)	(0.012)	(0.007)	(0.010)	(0.008)	(0.004)	(0.019)	(0.013)	(0.010)
Modular-RC	0.476	0.199	0.819	0.126	0.059	0.656	0.577	0.325	0.620	0.469	0.221	0.754	0.214	0.148	0.575
	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.006)	(0.005)	(0.004)
DEC	0.665	0.406	0.926	0.611	0.477	0.888	0.529	0.391	0.744	0.590	0.323	0.895	0.116	0.134	0.567
	(0.032)	(0.021)	(0.014)	(0.037)	(0.045)	(0.019)	(0.030)	(0.025)	(0.015)	(0.018)	(0.027)	(0.010)	(0.051)	(0.033)	(0.024)
GRAIL	<u>0.742</u>	<u>0.608</u>	<u>0.961</u>	<u>0.703</u>	<u>0.581</u>	<u>0.917</u>	0.538	0.309	0.673	0.774	0.699	0.832	0.203	0.112	0.577
	(0.008)	(0.007)	(0.003)	(0.010)	(0.009)	(0.005)	(0.012)	(0.011)	(0.014)	(0.007)	(0.006)	(0.004)	(0.021)	(0.013)	(0.009)
Time2feat	0.686	0.410	0.905	0.610	0.417	0.869	0.654	0.600	0.873	<u>0.921</u>	<u>0.822</u>	<u>0.966</u>	0.003	0.001	0.498
	(0.015)	(0.017)	(0.016)	(0.018)	(0.015)	(0.009)	(0.020)	(0.019)	(0.008)	(0.010)	(0.008)	(0.000)	(0.001)	(0.001)	(0.005)
TimesURL	0.655	0.403	0.919	0.135	0.028	0.554	0.515	0.399	0.712	0.415	0.344	0.703	0.126	0.148	0.574
	(0.018)	(0.015)	(0.007)	(0.020)	(0.008)	(0.010)	(0.022)	(0.018)	(0.012)	(0.015)	(0.012)	(0.009)	(0.025)	(0.020)	(0.016)
TFMCC	0.647	0.409	0.922	0.188	0.067	0.698	0.625	0.468	0.766	0.506	0.243	0.853	0.167	0.211	0.605
	(0.016)	(0.014)	(0.006)	(0.018)	(0.009)	(0.011)	(0.020)	(0.015)	(0.010)	(0.014)	(0.011)	(0.008)	(0.028)	(0.022)	(0.014)
GB-SMKKM	0.559	0.338	0.931	0.234	0.112	0.807	0.692	0.558	0.840	0.895	0.761	<u>0.966</u>	0.207	<u>0.263</u>	<u>0.631</u>
	(0.005)	(0.004)	(0.002)	(0.006)	(0.005)	(0.004)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.002)	(0.008)	(0.007)	(0.005)
MV-CAGAF	0.529	0.467	0.868	0.695	0.235	<u>0.917</u>	0.650	0.526	0.843	0.774	<u>0.636</u>	<u>0.930</u>	0.232	0.161	0.585
	(0.006)	(0.005)	(0.003)	(0.008)	(0.006)	(0.004)	(0.009)	(0.008)	(0.006)	(0.005)	(0.005)	(0.003)	(0.010)	(0.009)	(0.007)
MSRGC-Net	0.789	0.645	0.964	0.781	0.750	0.948	0.678	0.615	<u>0.857</u>	0.929	0.884	0.983	<u>0.225</u>	0.270	0.635
	(0.003)	(0.006)	(0.001)	(0.004)	(0.003)	(0.001)	(0.001)	(0.005)	(0.004)	(0.002)	(0.002)	(0.000)	(0.006)	(0.006)	(0.004)

Table 1: Clustering results on multivariate time series datasets. Abbreviations: CT - CharacterTrajectories; JV - JapaneseVowels; BM - BasicMotions; Cric - Cricket; SCP1 - SelfRegulationSCP1.

Variants	Multiscale Reservoirs	Granular-ball Anchoring	Explicit Optim.	Multivariate Datasets					Univariate Datasets				
				CT	JV	BM	Cric	SCP1	BC	Crop	EPG-R	EPG-S	Wafer
1. w/o Multiscale	×	✓	✓	0.943	0.785	0.844	0.944	0.581	0.738	0.926	0.993	0.997	0.559
2. w/o Granular-ball	✓	×	✓	0.953	0.920	0.832	0.970	0.579	0.740	0.922	1.000	0.984	0.561
3. w/o Optimization	✓	✓	×	0.952	0.936	0.811	0.966	0.559	0.713	0.894	0.962	0.958	0.490
MSRGC-Net (Ours)	✓	✓	✓	0.964	0.948	0.857	0.983	0.635	0.759	0.941	1.000	1.000	0.575

Table 2: Ablation study results evaluated using the RI metric.

performance without iterative training. Overall, these observations suggest that the proposed consensus learning framework is effective for multivariate time series clustering.

4.2 Ablation Studies

To analyze the contribution of each component, we compare MSRGC-Net with three ablated variants: (1) **w/o Multiscale**, where all reservoirs share a fixed spectral radius of 0.9 to remove multi-scale dynamics; (2) **w/o Granular-ball**, where adaptive granular-ball construction is replaced by k -means clustering for anchor selection; (3) **w/o Optimization**, where the optimization objective (Eq. 8) is replaced by simple average fusion.

Table 2 summarizes the ablation results in terms of the RI metric. On the multivariate datasets, the full MSRGC-Net achieves the highest average RI (0.883), outperforming the w/o Multi-scale, w/o Granular-ball, and w/o Optimization variants by clear margins. Similar trends are observed on univariate datasets, where the full model consistently achieves the best or tied-best performance. This demonstrates that all components contribute to the final clustering performance, with the multi-scale mechanism playing a dominant role,

while granular-ball anchors and optimization-based fusion further enhance the results.

4.3 Visualization Analysis

Figure 3 visualizes the learned representations of the proposed model on the JV multimodal dataset. On the left, t-SNE projects the samples into a low-dimensional space, where three representative clusters (Class 1/2/3) are identified for further analysis, showing a clear separation in the learned representation space. The top-right panel illustrates the trajectories of samples within each cluster (blue: individual samples; orange: cluster mean). The bottom-right panel presents ESN state heatmaps with spectral radii $SR=0.8$ and $SR=1.0$, which provide a more fine-grained view of the underlying dynamical representations.

Green markers highlight early-stage differences between Class 1 and Class 2, with distinct temporal dynamics. Red markers indicate mid-stage differences between Class 1 and Class 3, showing clear dynamical changes. A vertical comparison across spectral radii reveals complementary temporal patterns: smaller SR emphasizes local transient variations, whereas larger SR captures longer-term dependencies.

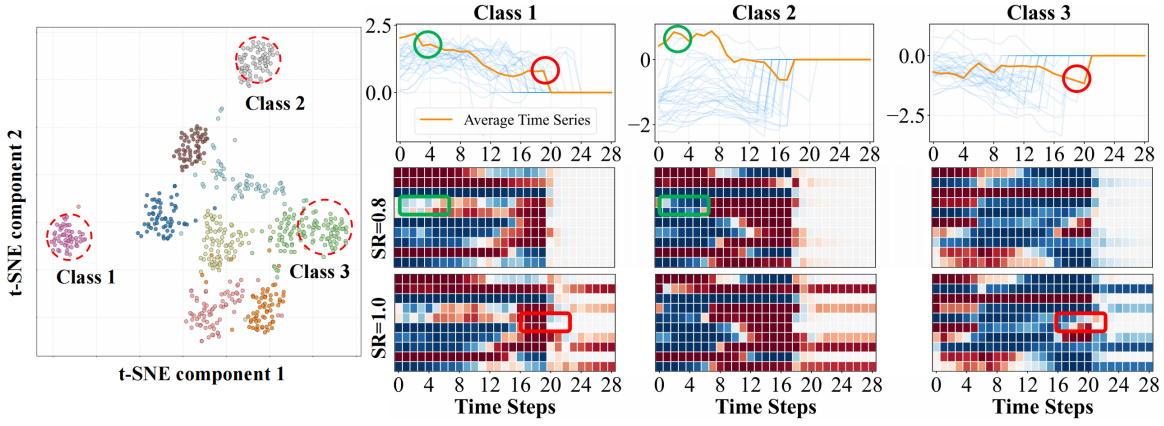


Figure 3: Visualization of complementary representations from multi-scale reservoirs, where green and red annotations indicate characteristic dynamical differences across clusters.

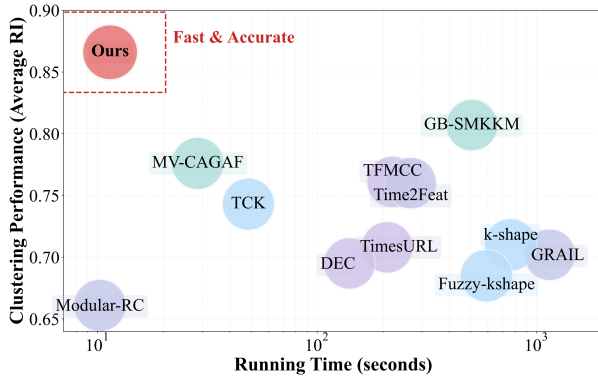


Figure 4: Running time versus clustering effectiveness.

This suggests that the multi-scale design enables the model to encode diverse temporal characteristics, thereby enhancing cluster separability in multimodal time-series data.

4.4 Efficiency–Effectiveness Analysis

Figure 4 presents an efficiency–effectiveness comparison of all methods across ten datasets spanning both univariate and multivariate settings. The y-axis reports the average RI, while the x-axis shows the average running time on a logarithmic scale. Overall, our method lies in the upper-left region of the plot and on the Pareto frontier, indicating a favorable trade-off between clustering performance and computational cost. It achieves high clustering accuracy with a runtime on the order of tens of seconds. In contrast, several baseline methods incur substantially higher computational costs without corresponding performance gains. Compared with the second-best method, GB-SMKKM, our approach achieves superior performance with roughly an order-of-magnitude lower runtime. Moreover, the comparison with rm-ESN highlights the benefit of multi-view reservoir dynamics over single-view representations.

Large-scale testing. We further evaluate scalability on an extended Pedestrian dataset containing approximately 1.8 million samples. As shown in Figure 5, the runtime increases

near-linearly with the sample size and remains stable even at the million-sample scale. MSRGC-Net achieves an RI of 0.947 ± 0.002 , outperforming k-shape (0.882 ± 0.004), indicating that improved scalability does not come at the expense of clustering quality. This empirical observation is consistent with the theoretical time complexity $\mathcal{O}(VNTR^2 + NR + Nm^2)$, where $m \ll N$, implying near-linear growth with respect to N .

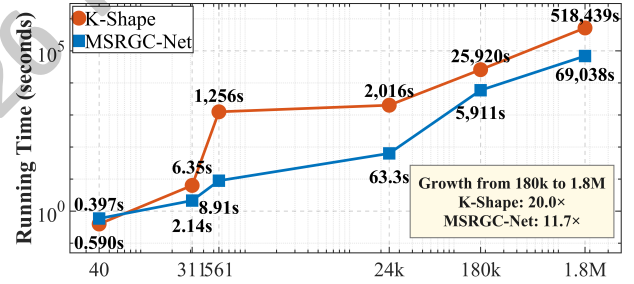


Figure 5: Scalability evaluation on million-scale samples.

5 Conclusion

We proposed MSRGC-Net, a multi-scale reservoir-based graph clustering framework for efficient time-series clustering. By employing training-free reservoirs with diverse spectral radii, the model captures complementary temporal dynamics ranging from local transient patterns to long-term dependencies. These multi-scale representations are integrated via granular-ball-based anchor construction and a consensus graph optimization scheme, enabling effective fusion of multi-view temporal information. Extensive experiments on both univariate and multivariate datasets demonstrate that MSRGC-Net consistently outperforms state-of-the-art methods. Ablation and visualization analyses further validate the contribution of each component and reveal how the multi-scale design enhances cluster separability. Moreover, efficiency–effectiveness analysis shows that MSRGC-Net achieves a favorable balance between clustering accuracy and computational cost.

Acknowledgments

This research was supported by the Chongqing Graduate Research Innovation Program CYB25259 and the National Natural Science Foundation of China under Grant Nos. 62221005, 62450043, 62222601, and 62176033.

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