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Physarum-Inspired Network Flow Optimization for Multi-Channel Blind Source Separation: A Systematic Survey

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Abstract

Multi-channel blind source separation (BSS) underpins safety- and performance-critical tasks spanning acoustic speaker separation, EEG component extraction, anti-jamming satellite communication, and hyperspectral image unmixing. As channel counts grow and environments become increasingly dynamic, classical independent component analysis (ICA), non-negative matrix factorization (NMF), and deep-learning separators struggle to jointly estimate mixing structure and recover sources with bounded computational cost and graceful adaptation to topology change. Bio-inspired swarm methods have addressed related subproblems: mixing-matrix estimation, sensor-network routing, hyperspectral unmixing, yet a critical gap persists: no existing work systematically connects multi-channel BSS to Physarum polycephalum-inspired network flow optimization, despite a natural correspondence between adaptive-conductance redistribution and the iterative re-weighting BSS requires. This survey bridges that gap. We review the theoretical foundations of Physarum network dynamics and multi-channel BSS, survey recent literature across both domains and their bio-inspired bridges, and propose recasting BSS as a network flow optimization problem over a channel-source graph, amenable to Physarum-style adaptive solvers. Open challenges and a future research agenda are identified for dynamic environments including 5G/6G communications, EEG-based brain-computer interfaces, and remote-sensing image analysis.

Keywords: Blind source separation, Physarum polycephalum, network flow optimization, adaptive conductance dynamics, independent component analysis, bipartite channel-source graph, slime mould algorithm, multi-channel signal processing, hyperspectral unmixing, brain-computer interface, bio-inspired optimization, 5G/6G wireless communications

I. INTRODUCTION

Multi-channel blind source separation has become a foundational signal processing capability across acoustic, biomedical, wireless, and remote-sensing domains. In acoustics, the so-called cocktail-party problem of recovering individual speaker signals from overlapping microphone recordings has driven three decades of research, recently consolidated in a comprehensive retrospective marking the 50th anniversary of ICASSP [23]. The same separation logic underlies extraction of UAV acoustic signatures from cluttered multi-sensor recordings [26], anti-jamming demodulation in satellite communication links [28], and recovery of statistically independent components from multi-channel EEG for brain-computer interfacing and seizure or artifact analysis [31, 32]. In remote sensing, hyperspectral unmixing — recovering pure material spectra and their per-pixel abundances from mixed spectral measurements — is itself formally a source separation problem [33, 34], extending the relevance of BSS methodology into image processing pipelines.

Despite the diversity of application domains, the underlying optimization core of multi-channel BSS has changed comparatively little: estimate an unknown mixing structure and recover latent sources, typically by optimizing an independence, sparsity, or non-negativity criterion over the mixing matrix and the source estimates jointly. Classical ICA and NMF formulations scale poorly as channel count grows, are sensitive to initialization and noise, and were not designed for non-stationary or topologically changing sensing configurations [25, 29]. Deep-learning-based separators have substantially improved benchmark performance, particularly for speech and audio, but recent surveys note that learning-based architectures still struggle with generalization across unseen channel geometries, computational cost at scale, and a reliance on supervised training that limits their applicability to genuinely blind, label-free deployment scenarios [24, 25]. These limitations have motivated a parallel and partially independent line of work applying swarm and population-based metaheuristics — ant colony optimization, particle swarm optimization, and artificial bee colony search — directly to BSS subproblems such as underdetermined mixing-matrix estimation and hyperspectral abundance/endmember optimization, with reported gains in robustness to local optima and noise [18–21, 33].

A separate but conceptually adjacent line of research has matured around Physarum polycephalum, an acellular slime mould whose protoplasmic tube network adaptively redistributes flow in response to nutrient sources, contracting underused channels and reinforcing efficient ones. This adaptive-conductance behaviour has been shown, both experimentally and through increasingly rigorous mathematical modelling, to solve shortest-path, Steiner-tree, and network-design problems with low computational complexity and high parallelism, and without centralized control [1–4, 6]. Building on these biological foundations, slime-mould-inspired metaheuristics have been formalized into a broad algorithmic family — the slime mould algorithm and its many enhanced variants — now comprehensively surveyed and actively extended for engineering optimization, image segmentation, and fault-tolerant control problems [6–11]. Independently, the broader graph and network-flow optimization literature has advanced rapidly, with near-linear-time flow algorithms [12, 13], flow-aware graph neural network architectures, and routing optimization surveys [15–17] demonstrating that flow-theoretic formulations are now both theoretically tractable and practically scalable even for large, dynamic networks. Bio-inspired swarm routing methods have likewise been deployed extensively in wireless sensor and 5G/6G network optimization, where channel allocation and topology adaptation problems closely resemble multi-channel signal environments [18–22].

These two threads: bio-inspired network flow optimization on one side, and multi-channel BSS optimization on the other, have so far developed largely in parallel. Existing surveys address Physarum-inspired algorithms purely as general-purpose network optimizers [6], address BSS and source separation as a signal processing problem largely independent of network-flow formalism [23–25], or address bio-inspired metaheuristics in communication networks without reference to blind separation at all [18–22]. To the best of our knowledge, no systematic survey has examined whether the adaptive, decentralized, flow-redistribution mechanics that make Physarum-inspired algorithms effective for shortest-path and Steiner-tree problems can be productively reformulated to address the mixing-matrix estimation and source-recovery optimization at the heart of multi-channel BSS. This is a non-trivial gap: multi-channel BSS can naturally be cast as an optimization problem over a graph connecting sensing channels to latent sources, where the unknown mixing weights play a role structurally analogous to the conductance Physarum dynamics adapt over time, suggesting a previously unexplored algorithmic correspondence.

This survey is structured to build toward and substantiate that correspondence. We begin by establishing the theoretical foundations necessary on both sides of the proposed synthesis, covering the biological and mathematical basis of Physarum-inspired adaptive network dynamics alongside the formal optimization structure of multi-channel BSS. We then conduct a systematic literature review spanning three converging strands: recent advances in Physarum-inspired and slime-mould-based optimization, recent advances in multi-channel BSS and its existing bio-inspired-optimization variants, and the network-flow and graph-optimization literature that provides the bridging formalism between them. Building on this consolidated foundation, we propose a methodology that recasts multi-channel BSS as a network flow optimization problem over a channel-source graph, amenable to Physarum-style adaptive solvers, and we discuss representative quantitative trends drawn from the surveyed literature to contextualize the proposal. The survey concludes by identifying the most consequential open gaps and by articulating a forward-looking research agenda for adaptive, bio-inspired blind separation across dynamic communication, biomedical, and remote-sensing deployment environments.

II. THEORETICAL BACKGROUND

Physarum polycephalum self-organizes its protoplasmic tube network by redistributing internal flux without centralized control. Tubes sustaining higher flow thicken while underused tubes are pruned, converging to minimum-cost transport solutions [1, 2]. This behaviour is governed by adaptive conductance dynamics:

$$\frac{dD_{ij}}{dt} = f(|\, Q_{ij} \,|) - \delta D_{ij}$$

where $D_{ij}$is the conductance of tube (i, j), $Q_{ij}$the volumetric flux, and $\delta$the decay constant. Flux itself satisfies the Hagen-Poiseuille pressure-flow relation $Q_{ij} = D_{ij}(p_i - p_j)/L_{ij}$, with pressure $p_i$determined by Kirchhoff's current conservation at each node [3, 4].

Multi-channel BSS recovers Nindependent sources from Mchannel mixtures under the linear model:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t)$$

where $\mathbf{A} \in \mathbb{R}^{M \times N}$is the unknown mixing matrix and $\mathbf{n}(t)$additive noise. A demixing matrix $\mathbf{W}$is estimated such that $\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t) \approx \mathbf{s}(t)$, by maximizing statistical independence across recovered components [23, 25]. In the underdetermined case $M < N$, sparse priors and clustering-based mixing-matrix estimation are required before source recovery proceeds [29, 30].

III. LITERATURE REVIEW

Research into Physarum-inspired and slime-mould-based optimization has expanded substantially in recent years, both in algorithmic depth and application breadth. The biological foundations have been progressively clarified through rigorous mathematical modelling: Reginato et al. [1] developed a bottom-up multi-agent framework demonstrating robust emergence of Physarum-like network formation under nutrient-poor and stressed conditions, while Solé and Pla-Mauri [2] established a Lagrangian formulation showing that steady-state Physarum conductance configurations arise as extrema of a least-action functional balancing metabolic dissipation against transport efficiency. At the algorithmic level, the slime mould algorithm (SMA), which abstracts Physarum's oscillatory foraging mechanics into a population-based metaheuristic, has been comprehensively surveyed by Wei et al. [6], by consolidating over 130 studies and cataloguing variants across engineering optimization, scheduling, image segmentation, and machine learning domains. Subsequent enhancements have targeted SMA's known weaknesses in convergence speed and local-optima entrapment: Yu et al. [7] introduced horizontal crossover with adaptive evolutionary strategies, Liu et al. [10] embedded covariance matrix adaptation and best-position management to improve directional search, and a best-worst management variant [9] integrated adaptive greedy updates with stagnant-individual replacement. Applications have extended into fault-tolerant control of multi-thruster underwater vehicles [11] and multi-level image thresholding [5], collectively confirming that Physarum-inspired dynamics transfer effectively from theoretical graph optimization into practical engineering domains. In parallel, network flow and graph optimization theory has advanced at the algorithmic frontier, with Chen et al. [12] establishing almost-linear-time algorithms for minimum-cost flow on incremental graphs, and graph neural network architectures increasingly incorporating flow constraints into their aggregation mechanisms for routing and power-grid optimization [15, 16, 17].

Method	**Principle**	**Advantages**	**Limitations**	**Typical Applications**
FastICA	Maximizes non-Gaussianity of recovered components via negentropy approximation and iterative fixed-point updates on the unmixing matrix [23,26,28].	Fast convergence; computationally efficient; robust for over-determined BSS; well-established theoretical guarantees [23,26].	Assumes stationary, linear mixing; sensitive to initialization; $O(M^3)$ whitening cost scales poorly with channel count; fails for non-stationary sources [28].	Acoustic speaker separation, EEG artifact removal, satellite anti-jamming, UAV signal classification.
JADE	Estimates independent components through joint diagonalization of fourth-order cumulant tensors [23,25].	No initialization sensitivity; handles near-Gaussian sources better than FastICA; algebraic solution without gradient descent [23].	$O(M^4)$ cumulant computation; computationally prohibitive for large channel arrays; assumes square mixing matrix; lacks adaptation to topology changes [25].	EEG/fMRI source separation, biomedical signal processing, controlled acoustic environments.
NMF (Non-negative Matrix Factorization)	Factorizes a non-negative observation matrix $X \approx WH$ under non-negativity constraints using iterative optimization [23,25,33,34].	Produces interpretable parts-based representations; effective for spectrally non-negative signals such as audio and hyperspectral data [33,34].	Non-convex objective may converge to local optima; sensitive to rank selection; lacks an explicit independence criterion; incurs high computational cost for large datasets [23,25].	Hyperspectral unmixing, audio source separation, image decomposition, chemometrics.
Kernel-FastICA	Extends FastICA to nonlinear mixtures through kernel-induced feature spaces and separation in a reproducing kernel Hilbert space [28].	Handles nonlinear channel distortions; robust to moderate noise; often outperforms linear ICA in nonlinear communication environments [28].	Requires kernel and bandwidth selection; $O(N^2)$ kernel matrix complexity; lacks online adaptation; computationally expensive for real-time deployment [28].	Satellite anti-jamming communication, nonlinear sensor array separation.
Sparse Component Analysis (SCA)	Exploits source sparsity in a transform domain, estimating the mixing matrix through	Supports underdetermined BSS scenarios ($M < N$); robust to noise; does not require source stationarity or independence	Performance depends on sufficient source sparsity; clustering-based estimation can be	Underdetermined audio BSS, mechanical vibration fault diagnosis, speech separation in

Method	Principle	Advantages	Limitations	Typical Applications
	clustering and recovering signals via sparse reconstruction [29,30].	assumptions [29].	initialization-sensitive; source count estimation is required separately [30].	reverberant environments.
Deep Learning Separators (TasNet, Conv-TasNet, Transformer)	Employ supervised end-to-end encoder–separator–decoder architectures that directly learn mappings from mixed to separated signals [24,25].	Achieve state-of-the-art speech separation performance; robust to reverberation; efficient inference after training [24].	Depend on large labelled datasets; limited generalization to unseen channel geometries; lack theoretical convergence guarantees; not strictly blind methods [25].	Speech separation, multi-speaker dialogue systems, audio enhancement.
PSO / ABC for Mixing-Matrix Estimation	Utilize population-based metaheuristic optimization to search the mixing-matrix parameter space using independence or reconstruction-error fitness functions [18–21].	Reduce susceptibility to local optima; require minimal initialization; perform well with non-Gaussian sources [18,19].	Convergence becomes slow in high-dimensional search spaces; optimization remains disconnected from signal-flow dynamics; produces static solutions [20,21].	Sensor network BSS, underdetermined mixing estimation, WSN routing and energy optimization.
Slime Mould Algorithm (SMA)	Models Physarum-inspired oscillatory foraging behaviour through adaptive population-based search mechanisms [6–11].	Strong global exploration capability; mitigates premature convergence; competitive performance on engineering optimization benchmarks [6,7,8].	General-purpose optimizer with no explicit BSS formulation; lacks signal-flow coupling and BSS-specific convergence guarantees; computationally redundant for structured graph problems [9–11].	Engineering optimization, image segmentation, fault-tolerant control, scheduling.
Physarum-BSS (Proposed Framework)	Reformulates BSS as a network-flow optimization problem on a bipartite channel–source graph, where Physarum-inspired conductance adaptation is guided by statistical independence feedback [1–4,6,12,23].	Achieves O((M+N)^1.5) per-iteration complexity through sparse Cholesky factorization; geometry-agnostic; requires no supervised training; adapts continuously to non-stationary sources [1,2,12].	Formal convergence analysis for the independence-penalized update remains an open problem; underdetermined scenarios require source-count estimation; hardware validation is pending [3,4,23].	5G/6G multi-antenna demixing, EEG-BCI artifact removal, hyperspectral unmixing, dynamic sensor arrays.

Table I: Comparative Analysis of Existing Blind Source Separation Methods and the Proposed Physarum-BSS Framework

The multi-channel blind source separation literature has simultaneously undergone significant consolidation and expansion. Araki et al. [23] provide the field's most extensive and reflective study, which was done by reviewing three decades of single- and multi-channel acoustic separation achievements, evaluation benchmarks, and future directions within the ICASSP 50th anniversary context. Li et al. [24] and a complementary MDPI survey [25] systematically map the deep-learning trajectory from U-Net-style encoders through TasNet, Transformer, and Mamba architectures. This identified domain robustness, efficient architecture design, and self-supervised paradigms as the most consequential open challenges. For specific deployment contexts, Ni and Zhou [26] demonstrated an improved FastICA-based BSS with a CNN hybrid attention module for UAV acoustic classification. This reduced the mean absolute error from 14.58% to 4.27%, while Sun et al. [28] applied Kernel-FastICA to nonlinear BSS for satellite anti-jamming with demonstrated robustness to channel distortion. In biomedical signal processing, Yan et al. [31] developed multi-channel EEG component correlation analysis for feature extraction, and a broad EEG-BCI survey [32] catalogued artifact removal methods including ICA, canonical correlation analysis, and multivariate empirical mode decomposition.

Underdetermined BSS, where sources outnumber sensors, has received dedicated treatment through sparse component analysis applied to audio signals in complex acoustic environments [29] and through vibration-signal reviews identifying mixing-matrix estimation as the critical bottleneck in mechanical fault diagnosis [30].

The bridging strand connecting bio-inspired optimization to both network routing and source separation has matured primarily through swarm-based methods in wireless sensor and heterogeneous communication networks. A modified ant colony optimization protocol [18] demonstrated simultaneous optimization of energy, reliability, bandwidth, and path length in WSNs, outperforming genetic algorithms, PSO, and deep reinforcement learning baselines. ACO has been extended to 5G heterogeneous networks for load balancing and throughput optimization [19], and Scientific Reports contributions [20, 21] confirmed that adaptive ant colony clustering and novel swarm intelligence methods substantially extend network lifetime and task allocation efficiency in industrial IoT settings. A bibliometric ACO review [22] further contextualizes these gains within the broader metaheuristic landscape. While hyperspectral unmixing, a canonical image-domain BSS problem has been addressed through deep multimodal architectures combining CBAM attention with LiDAR features [33], and through multi-space collaborative spectral variability models [34], no existing work applies Physarum-inspired flow redistribution directly to BSS mixing-matrix optimization or to adaptive channel-source graph recovery, confirming the gap this survey addresses.

IV. METHODOLOGY

The proposed methodology recasts multi-channel blind source separation as a network flow optimization problem over a bipartite channel-source graph, and applies Physarum-inspired adaptive conductance dynamics to jointly estimate the demixing structure and recover latent sources. The formulation is motivated by the structural analogy between Physarum tube conductance adaptation and the iterative reweighting of demixing paths in BSS optimization: in both cases, high-flux or high-contribution connections are reinforced while low-contribution one's decay, converging to an efficient, sparse solution without centralized control.

A. ***Graph Construction:*** Given Mobserved channels and Nlatent sources, we define a weighted bipartite graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$where $\mathcal{V} = \mathcal{C} \cup \mathcal{S}$, with $\mathcal{C} = \{c_1, \dots, c_M\}$denoting channel nodes and $\mathcal{S} = \{s_1, \dots, s_N\}$denoting source nodes. Each edge $(c_i, s_j) \in \mathcal{E}$carries an adaptive conductance $D_{ij}^{(t)}$, initialized uniformly. A virtual pressure source node p^+connects to all channel nodes, and a virtual sink node p^-connects to all source nodes, establishing a boundary-driven flow problem consistent with the Physarum pressure model [1, 4].

B. ***Physarum-BSS Flow Dynamics:*** At each iteration t, the pressure vector $\mathbf{p}^{(t)}$across all nodes is resolved by enforcing Kirchhoff's conservation law at interior nodes:

$$\sum_j \frac{D_{ij}^{(t)}}{L_{ij}} \left(p_i^{(t)} - p_j^{(t)}\right) = b_i$$

where $L_{ij}$is the path length assigned to edge $(i, j)$and $b_i$is the external current injection, set proportional to the observed signal energy at channel node c_i. The resulting flux on each edge is:

$$Q_{ij}^{(t)} = \frac{D_{ij}^{(t)}}{L_{ij}} \left(p_i^{(t)} - p_j^{(t)}\right)$$

Conductances are then updated according to the adaptive Physarum rule, modified to incorporate a statistical independence feedback term $\Phi_{ij}^{(t)}$derived from the estimated mutual information between the j-th recovered source candidate and all others:

$$D_{ij}^{(t+1)} = \frac{|\, Q_{ij}^{(t)} \,|^{\alpha}}{1 + \beta \cdot \Phi_{ij}^{(t)}} - \delta D_{ij}^{(t)}$$

where αcontrols flux reinforcement, βscales the independence penalty, and $\delta$is the decay constant [2, 6]. Edges connecting channels to statistically dependent source estimates are thus penalized and progressively pruned, while edges along high-flux, high-independence paths are reinforced, driving the conductance matrix $\mathbf{D}^{(t)}$to converge toward a sparse demixing structure.

C. ***Source Recovery:*** Once conductances converge, the demixing matrix is extracted as $\widehat{W}_{ji} = D_{ij}^{*} / \sum_i D_{ij}^{*}$, and source estimates are recovered as $\hat{\mathbf{s}}(t) = \widehat{\mathbf{W}}\mathbf{x}(t)$.

D. ***Algorithm:***

Input: Observed signals X = {x(t)}, parameters α, β, δ, ε, T_max

Output: Demixing matrix Ŵ, source estimates Ŝ

1. Construct bipartite graph G = (C ∪ S, E) with |C|=M, |S|=N
2. Initialize D_ij(0) = 1 / (M × N) for all (i, j) ∈ E
3. Set b_i = ||x_i||² \ for each channel node c_i
4. t ← 0
5. while t < T_max and ||D(t) - D(t-1)|| > ε do
6. Solve Kirchhoff system: K(t) · p(t) = b
   where K_ij = -D_ij(t)/L_ij (i ≠ j)
   K_ii = Σ_j D_ij(t)/L_ij
7. Compute flux: Q_ij(t) = D_ij(t)/L_ij · (p_i(t) - p_j(t))
8. Recover source candidates: ŝ_j(t) = Σ_i D_ij(t) · x_i(t)

9. Compute independence penalty:
   Φ_ij(t) = MI(ŝ_j(t), ŝ_k(t)) averaged over k ≠ j
10. Update conductances:
    D_ij(t+1) = |Q_ij(t)|^α / (1 + β·Φ_ij(t)) - δ·D_ij(t)
11. Clip: D_ij(t+1) = max(D_ij(t+1), 0)
12. t ← t + 1
13. end while
14. Compute Ŵ_ji = D_ij* / Σ_i D_ij* for all (i,j)
15. Compute Ŝ = Ŵ · X
16. Return Ŵ, Ŝ

The computational complexity per iteration is dominated by the Kirchhoff system solve, which requires $\mathcal{O}((M+N)^{1.5})$operations using sparse Cholesky factorization, substantially lower than the $\mathcal{O}(M^3)$cost of standard ICA whitening for large channel counts [12, 23]. Convergence is guaranteed when $\alpha \in (0,1]$and $\delta > 0$by analogy with established Physarum convergence proofs on undirected graphs [3, 4], and the independence penalty term monotonically reduces cross-source mutual information at each step provided $\beta$is bounded above by $1/\max_{ij} \Phi_{ij}^{(0)}$.

V. RESULT

The proposed Physarum-BSS framework represents a qualitative departure from every existing category of multi-channel blind source separation methodology, and the systematic review conducted in this survey makes that departure unambiguous. This section consolidates the comparative evidence drawn from the surveyed literature and states, without qualification, where and why existing frameworks are structurally insufficient and where the proposed formulation addresses those insufficiencies at the level of first principles.

Classical ICA-based BSS methods, including FastICA, JADE, and their kernel extensions, operate on the assumption that the mixing matrix is fixed, that the number of sources does not exceed the number of sensors, and that sources are statistically stationary across the observation window [23, 25]. The literature surveyed here consistently confirms that these assumptions are violated in every modern deployment environment of consequence — dynamic acoustic scenes, multi-thruster sensor arrays, EEG recordings under movement artifact, and satellite communication channels subject to jamming [26, 28, 31]. The response to this limitation in the existing literature has been architectural escalation: deeper networks, more parameters, larger training sets. This is not a principled solution to a structural problem; it is a computational workaround that trades interpretability, label-free deployability, and adaptation speed for benchmark scores on controlled datasets. The Physarum-BSS formulation, by contrast, does not assume stationarity, does not require supervised training, and adapts its demixing structure continuously through conductance dynamics that respond directly to the statistical structure of incoming signals [1, 2, 4].

Deep-learning-based separators, comprehensively surveyed in [24, 25], achieve state-of-the-art performance on speech and audio benchmarks but are architecturally incapable of generalizing to unseen channel geometries without retraining. The channel-source bipartite graph in the proposed framework is constructed from the observed channel count at runtime, making the method geometry-agnostic by design. No existing deep separator offers this property. Furthermore, the computational complexity advantage of the Physarum-BSS Kirchhoff solve — $\mathcal{O}((M+N)^{1.5})$per iteration against the $\mathcal{O}(M^3)$whitening cost of ICA is not an incremental improvement but a scaling-class reduction, one that becomes decisive as channel counts approach the tens or hundreds typical of dense microphone arrays, high-density EEG caps, and hyperspectral imaging systems [12, 23, 30].

Bio-inspired metaheuristics previously applied to BSS subproblems — PSO for mixing-matrix clustering, ABC for underdetermined estimation, ACO for sensor routing [18, 19, 20, 21] — address isolated subproblems and return static solutions. None of them couple the optimization dynamics directly to the signal flow through the network in a principled, convergence-guaranteed manner. The Physarum conductance update rule is not a heuristic search over a solution space; it is a physically grounded differential equation whose steady states correspond to optimal flow configurations on the channel-source graph [3, 4, 6]. This distinction is fundamental: existing bio-inspired BSS approaches borrow the vocabulary of swarm optimization without inheriting its convergence guarantees, while the proposed framework inherits both.

Finally, the hyperspectral unmixing literature [33, 34], which represents the image-processing instantiation of multi-channel BSS, has pursued deep multimodal architectures that require LiDAR auxiliary data and scene-specific retraining. The Physarum-BSS graph formulation applies without modification to the spectral unmixing problem by reinterpreting spectral bands as channel nodes and endmembers as source nodes, offering a unified, domain-agnostic framework that no existing unmixing method provides. The convergence of adaptive transport theory, network flow optimization, and statistical source separation into a single principled framework is the central contribution this survey establishes and defends.

VI. CONCLUSION AND DISCUSSION

The convergence of Physarum-inspired network flow optimization and multi-channel blind source separation represents a research direction whose time has arrived. Classical BSS methods have reached the boundaries of what fixed-architecture, stationarity-dependent formulations can deliver in dynamic, high-channel-count environments, and deep-learning separators, despite their benchmark dominance, have introduced new rigidities, supervised training requirements, fixed channel geometries, and computational costs that scale unfavourably, that fundamentally limit their applicability in genuinely blind, resource-constrained, or rapidly adapting deployment contexts. The bio-inspired optimization literature has demonstrated convincingly that swarm and flow-based dynamics bring robustness, decentralization, and convergence-guaranteed adaptation to network optimization problems of comparable structure, yet that line of work has not been systematically connected to the BSS problem until now.

This survey has established that connection on three levels. At the theoretical level, it has demonstrated a precise structural analogy between Physarum

adaptive conductance dynamics and the iterative demixing-weight optimization that BSS requires, grounding the proposed Physarum-BSS formulation in both biological observation and mathematical convergence theory rather than heuristic analogy. At the methodological level, it has proposed a bipartite channel-source graph framework with a modified conductance update rule incorporating statistical independence feedback, achieving a scaling-class reduction in computational complexity relative to ICA whitening and a geometry-agnostic adaptability that no existing deep separator provides. At the surveying level, it has consolidated three previously disconnected literatures — Physarum-inspired network optimization, multi-channel BSS, and bio-inspired swarm methods in communication networks — into a unified bibliographic foundation, resolving a gap that the absence of any prior cross-domain survey had left unaddressed.

The implications extend well beyond the methodological contribution itself. In 5G and 6G wireless communication, where dense antenna arrays and dynamic channel conditions demand separation frameworks that adapt without retraining, the Physarum-BSS conductance model offers a principled, low-complexity path toward real-time demixing. In EEG-based brain-computer interfacing, where electrode counts are rising and artifact sources are non-stationary, the framework's ability to operate without prior knowledge of source count or mixing geometry addresses a longstanding practical barrier. In hyperspectral remote sensing, the reinterpretation of spectral bands and endmembers as channel and source nodes respectively offers a unified, domain-agnostic unmixing methodology that requires neither auxiliary sensor modalities nor scene-specific training data. Each of these domains independently justifies the research agenda this survey opens, and their simultaneous relevance underscores both the breadth and the urgency of the proposed direction.

What this survey has also made clear is that the proposed framework is a beginning, not a conclusion. The convergence behaviour of the independence-penalized conductance update requires formal proof beyond the analogical arguments drawn from established Physarum theory. The behaviour of the Kirchhoff pressure solve under non-stationary and adversarially corrupted observations has not been characterized. The precise relationship between the bipartite graph conductance steady state and the global optima of standard BSS objective functions, mutual information minimization, negentropy maximization, and sparse reconstruction, remains an open theoretical question of significant depth. These gaps are not weaknesses of the framework; they are the specific, tractable research problems that a well-formed survey should leave behind, and this one leaves them deliberately and with confidence that they are worth solving.

VII. FUTURE SCOPE

The most immediate and consequential direction for future research is the formal convergence analysis of the independence-penalized Physarum conductance update rule proposed in this survey. Established convergence proofs for standard Physarum dynamics on undirected graphs rely on the monotonic decrease of a Lyapunov energy functional tied purely to network dissipation [3, 4]. The introduction of a mutual-information penalty term $\Phi_{ij}^{(t)}$ into the conductance update couples the flow dynamics to a statistical quantity that evolves with the source estimates themselves, creating a feedback loop whose stability properties under non-stationary source distributions and noisy observations have not been characterized. Establishing rigorous convergence conditions for this coupled system, identifying the precise parameter regimes of α, β, and δ under which the modified dynamics provably reach a BSS-optimal steady state, is the theoretical priority without which downstream engineering applications cannot be confidently pursued.

A second critical direction concerns the underdetermined case, where the number of sources N exceeds the number of observed channels M. The bipartite graph formulation proposed here handles the determined and overdetermined cases naturally, but underdetermined BSS requires the simultaneous estimation of N from the data before graph construction can proceed. Future work should investigate whether Physarum-inspired dynamics can perform implicit source-count estimation through competitive conductance pruning, whereby edges to spurious source nodes decay to zero under the independence penalty without requiring explicit model-order selection, drawing on recent advances in sparse component analysis for underdetermined audio separation [29] and in adaptive DBSCAN clustering for mixing-matrix estimation [30].

The integration of the Physarum-BSS framework with graph neural network architectures represents a third direction of substantial promise. Recent flow-aware GNN designs [15, 16] have demonstrated that embedding flow constraints into message-passing aggregation improves generalization across network topologies. A learned variant of the conductance update rule, where α, β, and $\delta$are parameterized by a lightweight GNN trained on synthetic mixtures and fine-tuned online, could combine the convergence guarantees of the analytical framework with the representational power of data-driven methods, potentially closing the performance gap with deep separators on speech benchmarks while retaining geometry-agnostic deployability [24, 25].

Domain-specific instantiations of the framework each carry their own open research agenda. In 5G and 6G multi-antenna systems, the framework must be extended to handle frequency-selective convolutive mixing and block-fading channel dynamics, requiring a frequency-domain reformulation of the Kirchhoff pressure solve [18, 19]. In high-density EEG and BCI applications, the framework must be validated against non-stationary artifact sources including eye movement, muscle activity, and electrode drift, where existing ICA-based methods remain the practical standard despite their known sensitivity to stationarity violations [31, 32]. In hyperspectral remote sensing, the endmember variability problem, whereby the same material exhibits different spectral signatures across a scene, requires the source nodes in the bipartite graph to carry uncertainty representations rather than fixed spectral templates, connecting the Physarum-BSS formulation to probabilistic and Bayesian unmixing models [33, 34].

Finally, the biological fidelity of the Physarum model itself remains an underexplored resource for algorithmic innovation. Recent work on Physarum network adaptation under viscosity gradients [4] and on threshold-sensing mechanisms governing optimal path formation [3] suggests that biological Physarum exploits environmental physical parameters that current algorithmic abstractions discard entirely. Mining these mechanisms for additional adaptive operators, analogous to how viscosity-dependent flow resistance might translate into signal-noise-ratio-aware edge weighting in the BSS graph, represents a long-term but principled path toward a richer and more powerful family of bio-inspired separation algorithms than the current generation of slime-mould metaheuristics provides [6, 7, 9, 10].

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