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Towards the Development of an Enhanced Bacteria Foraging Optimization Algorithm for Feature-Level Fusion in Multibiometric Systems: A Systematic Literature Review

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Abstract

Unimodal biometric systems remain constrained by noisy acquisition, intra-class variability, non-universality, and susceptibility to spoofing, limitations that multibiometric systems address by combining evidence from two or more traits. Among the available integration strategies, feature-level fusion is widely regarded as the most information-rich, since it operates on the raw extracted feature sets before any matching decision is made, but it is also the most difficult to implement because of the curse of dimensionality, structurally incompatible feature spaces, and the absence of a known optimal combination rule. Metaheuristic search has emerged as a practical route through this difficulty, and the Bacteria Foraging Optimization Algorithm (BFOA) has attracted growing attention on account of its parallel search structure, insensitivity to initialization, and demonstrated effectiveness in feature selection tasks, despite well-documented weaknesses in convergence speed and premature stagnation. This paper presents a systematic literature review of feature-level fusion techniques and BFOA-based optimization in multibiometric authentication, covering studies published between 2013 and 2026 and drawn from IEEE Xplore, ScienceDirect, SpringerLink, MDPI, PubMed, and Google Scholar. Thirty-eight primary studies satisfied the inclusion criteria after a PRISMA-guided screening process. The review synthesizes the evolution of BFOA variants, chemotaxis-step and swarming modifications, and hybridizations with Lévy flight, particle swarm optimization, and chaotic search, alongside parallel developments in immune-based and evolutionary feature-selection methods applied to face, fingerprint, and iris fusion. The synthesis shows that although recognition accuracies exceeding 97% have been reported by several fusion frameworks, very few studies apply BFOA specifically at the feature level of a trimodal face-fingerprint-iris system, and fewer still address the algorithm's slow convergence and premature-stagnation weaknesses in that context. Building on these gaps, the review outlines a research direction for an Enhanced BFOA (EBFOA) that adapts the chemotactic step size across iterations and applies a non-uniform elimination-dispersal probability to preserve population diversity, intended to improve both recognition accuracy and computational efficiency in feature-level multibiometric fusion. The paper closes by identifying open questions for future primary research, including benchmark standardization, cross-dataset generalization, and real-time deployment feasibility.

Keywords: *Bacteria Foraging Optimization Algorithm; feature-level fusion; multibiometric systems; multimodal biometrics; metaheuristic optimization; systematic literature review.*

1. Introduction

Biometrics is the science of recognizing individuals on the basis of physiological or behavioural traits such as the face, fingerprint, iris, hand geometry, voice, gait, and signature. Physiological traits are generally regarded as more stable and reliable than behavioural ones because they are largely non-alterable, and among them the iris is often singled out as particularly distinctive and stable over a person's lifetime. Because biometric traits are unique, measurable, and largely permanent, biometric systems have progressively displaced possession-based tokens and knowledge-based credentials such as cards, keys, and passwords, which remain vulnerable to loss, theft, and compromise.

Most deployed biometric systems are, however, unimodal, relying on a single source of evidence such as a fingerprint or a face image. Unimodal recognition is susceptible to noisy sensor data, intra-class variation, inter-class similarity, non-universality, and spoofing, all of which inflate the False Accept Rate (FAR) and False Reject Rate (FRR) and impose an upper bound on achievable accuracy. Multibiometric systems, which combine two or more independent sources of biometric evidence, were introduced to overcome these constraints. Fusion in a multibiometric system can occur at the sensor, feature, matching-score, rank, or decision level, and among these, feature-level fusion has consistently been associated with the richest informational content and, in principle, the highest achievable recognition accuracy, because it operates on the extracted feature vectors themselves rather than on a summarized score or a hardened decision.

Realizing this theoretical advantage in practice is difficult. Concatenating feature vectors from heterogeneous modalities produces very high-dimensional composite vectors, a manifestation of the well-known curse of dimensionality; the relationship between features drawn from structurally dissimilar sources such as a Gabor-based fingerprint descriptor and a wavelet-based iris descriptor is not known a priori; and identifying an optimal, balanced combination of features across sources is itself a hard combinatorial search problem. These difficulties have motivated researchers to reformulate feature-level fusion as an optimization problem and to apply metaheuristic search algorithms, drawn from the immune-inspired, evolutionary, and swarm-intelligence families, to select and weight the fused feature set.

Among swarm-intelligence metaheuristics, the Bacteria Foraging Optimization Algorithm (BFOA), introduced by Passino (2002), models the chemotactic, swarming, reproduction, and elimination-dispersal behaviour of Escherichia coli bacteria foraging for nutrients. BFOA has been applied successfully to feature selection, clustering, scheduling, and control problems on account of its parallel, population-based search and its insensitivity to initialization. Classical BFOA nonetheless suffers from a fixed chemotaxis step size, an inefficient tumbling direction, slow convergence, and a tendency toward premature stagnation in high-dimensional, multimodal search landscapes of the kind encountered in trimodal feature-level fusion. This has, over roughly the last decade, generated a steady stream of enhanced BFOA variants, and a smaller but growing body of work applying BFOA and its relatives specifically to multibiometric feature fusion.

Despite the volume of work on both multibiometric feature-level fusion and BFOA enhancement considered separately, no systematic review to date has consolidated the two literatures to characterize how BFOA-family algorithms have actually been used, adapted, and evaluated for feature-level fusion of face, fingerprint, and iris traits. Existing surveys of multibiometric fusion tend to treat optimization algorithms briefly as one option among many (alongside score-level and decision-level alternatives), while surveys of BFOA variants are typically framed around generic benchmark functions or engineering-dispatch problems rather than biometric applications. This leaves a gap between what is known about improving BFOA in the abstract and what is known about applying it to the specific structural difficulties of trimodal feature-level fusion.

This review addresses that gap by systematically identifying, appraising, and synthesizing studies published between 2013 and 2026 that relate to: (i) feature-level fusion architectures and challenges in multibiometric systems; (ii) metaheuristic algorithms, with particular attention to BFOA and its variants, applied to feature selection and fusion; and (iii) the specific limitations of classical BFOA that later works have attempted to resolve. The review further synthesizes these findings into a set of research gaps and outlines the design direction for an Enhanced BFOA (EBFOA) intended for feature-level fusion of face, fingerprint, and iris modalities.

The contributions of this review are threefold. First, it provides a structured, PRISMA-guided synthesis of thirty-eight primary studies spanning classical and modern approaches to feature-level multibiometric fusion. Second, it traces the chronological evolution of BFOA variants from Passino's original formulation through chemotaxis-step, Lévy-flight, chaotic, and hybrid swarm modifications, situating these against the specific requirements of biometric feature fusion. Third, it distils the recurring, unresolved research gaps in the literature into concrete design requirements, motivating the enhancement strategy pursued in the associated primary study.

2. Literature Review

A biometric system is fundamentally a pattern recognition system that establishes or verifies identity from measured physiological or behavioural traits. Multimodal (or multibiometric) systems combine evidence from multiple sensors, multiple samples, multiple instances of the same trait, multiple feature-extraction algorithms, or multiple distinct traits, and can be arranged in serial, parallel, or hierarchical architectures. Parallel architectures, in which all modalities are captured and processed simultaneously before fusion, are generally preferred where strong authentication assurance is required, since they avoid the sequential dependency and cumulative latency of serial designs.

Sanderson and Paliwal's (2002) taxonomy separates biometric fusion into pre-mapping (pre-classification) and post-mapping (post-classification) categories. Pre-mapping fusion, which includes sensor-level and feature-level fusion, integrates information before any matcher produces an opinion. Post-mapping fusion, which includes fusion at the rank, matching-score, and decision (abstract) levels, integrates information after individual classifiers have already rendered a judgement. Decision-level fusion is the least informative because it discards all but the hardened output of each classifier, whereas feature-level fusion retains the richest representation of the raw biometric signal and is therefore associated with the greatest potential accuracy gain, at the cost of substantially higher implementation difficulty.

In feature-level fusion, the feature sets extracted from two or more sensors, or from a single sensor using multiple extraction algorithms, are concatenated or otherwise combined into a single composite feature vector prior to matching. The approach is attractive precisely because it operates closest to the raw signal, but it inherits several well-documented obstacles: the dimensionality of the concatenated vector grows rapidly with the number of modalities, degrading classifier performance (the curse of dimensionality); the statistical relationship between feature spaces drawn from structurally different extraction pipelines is not known in advance; maintaining a fair balance of influence across modalities of unequal discriminative strength is non-trivial; computational cost rises with vector size; and few chimeric multimodal databases exist for benchmarking, forcing many studies to rely on virtual (synthetically paired) multimodal datasets.

Because an exhaustive search for the optimal feature subset is combinatorially intractable, feature selection is commonly reframed as an optimization problem and addressed with metaheuristics, which trade a guarantee of global optimality for tractable, near-optimal solutions found through iterative, population-based search. Three broad families recur in the literature: immune-inspired algorithms such as the Clonal Selection Algorithm (CSA) and its Modified Clonal Selection Algorithm (MCSA) variant, which mimic antigen-driven affinity maturation; evolutionary algorithms such as the Genetic Algorithm (GA), which mimic natural selection, crossover, and mutation; and swarm-intelligence algorithms, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and BFOA, which mimic collective foraging or flocking behaviour. Each family has been applied to multibiometric feature selection with varying degrees of success, and hybridizations across families (for example BFOA-PSO or GA-fuzzy combinations) are increasingly common.

BFOA models a population of N bacteria executing four coupled processes: chemotaxis, in which each bacterium alternates between swimming (continuing in a favourable direction) and tumbling (choosing a new direction) in search of nutrient-rich, noxious-free regions of the search space; swarming, in which bacteria communicate through simulated attractant and repellent signals to coordinate collective movement; reproduction, in which the fitter half of the population (by accumulated fitness) is retained and cloned to replace the less fit half after a fixed number of chemotactic steps; and elimination-dispersal, in which bacteria are eliminated with a fixed probability and new bacteria are randomly reintroduced elsewhere in the search space to prevent stagnation around local optima.

The algorithm's principal strengths, insensitivity to initialization, structural simplicity, parallel and distributed search, and demonstrated robustness across network analysis, scheduling, economic dispatch, clustering, image processing, and feature selection, have driven its adoption. Its principal weaknesses, a fixed chemotaxis step size that cannot adapt as the search matures, an inefficient tumbling direction, and a fixed elimination-dispersal probability that treats all regions of the search space uniformly, translate into slow convergence and susceptibility to premature stagnation, especially on the nonlinear, high-dimensional, multimodal fitness landscapes typical of feature-level fusion across three or more biometric modalities. These weaknesses are the central motivation for the enhanced-BFOA literature reviewed in Section 4.

3. Methodology

This review followed the general reporting logic of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, adapted for a computing/engineering literature base rather than a clinical one.

The review questions are:

- RQ1: What fusion levels and architectures have been used for multibiometric authentication combining face, fingerprint, and iris traits?

- RQ2: Which metaheuristic algorithms, and which BFOA variants specifically, have been applied to feature selection or feature-level fusion in biometric systems?
- RQ3: What limitations of classical BFOA have been identified, and which mechanisms have been proposed to address them?
- RQ4: What research gaps remain in the application of BFOA-family algorithms to feature-level fusion of trimodal biometric systems?

Searches were conducted in IEEE Xplore, ScienceDirect, SpringerLink, MDPI, PubMed/PMC, ACM Digital Library, and Google Scholar, covering publications from January 2013 to February 2026. Search strings combined terms from three concept groups using Boolean operators: (i) biometric terms ("multimodal biometric", "multibiometric", "face fingerprint iris"); (ii) fusion terms ("feature-level fusion", "feature fusion", "early fusion"); and (iii) optimization terms ("bacterial foraging optimization", "BFOA", "BFO algorithm", "metaheuristic feature selection", "swarm intelligence"). Reference lists of retrieved articles were also hand-searched to identify additional eligible studies (backward snowballing).

Studies were included if they: (a) were published in a peer-reviewed journal, conference proceedings, or an indexed thesis/dissertation between 2013 and 2026; (b) addressed multibiometric or multimodal biometric fusion, or a BFOA/BFO variant applied to an optimization or feature-selection problem; and (c) reported at least one quantitative performance measure (accuracy, FAR, FRR, EER, or convergence behaviour) or a clearly described algorithmic modification. Studies were excluded if they: addressed unimodal biometrics only with no fusion component and no relevance to BFOA; were not available in English; were duplicate reports of the same dataset and method; or were opinion pieces, patents, or non-peer-reviewed preprints lacking sufficient methodological detail.

The search strategy returned an initial pool of records across the databases listed above. After removal of duplicates, titles and abstracts were screened against the inclusion criteria, followed by full-text assessment of the remaining candidates. Table 1 summarizes the screening funnel.

Table 1. Study selection funnel.

Stage	Records
Records identified through database searching	214
Additional records identified through backward snowballing	19
Records after duplicates removed	187
Records screened by title/abstract	187
Records excluded at screening stage	102
Full-text articles assessed for eligibility	85
Full-text articles excluded, with reasons	47
Studies included in the review	**38**

Each full-text candidate was appraised against four quality criteria: clarity of the stated research objective; adequacy of the description of the dataset and experimental setup; reporting of quantitative results with an identifiable baseline for comparison; and discussion of limitations or threats to validity. Studies satisfying at least three of the four criteria were retained.

For each included study, the following were extracted where reported: biometric modalities used, fusion level, optimization or classification algorithm, dataset(s), sample size, and headline performance figures (accuracy, FAR, FRR, EER, or convergence speed). Extracted data were synthesized narratively and thematically, organized around the review questions in Section 3.1, since the heterogeneity of datasets, modalities, and metrics across studies precluded a meta-analytic (pooled statistical) synthesis.

4. Results of the Review

The 38 included studies span 2013 to 2026, with a visible concentration from 2018 onward as deep-learning-assisted fusion and metaheuristic hybridization both accelerated. Face-iris and face-fingerprint pairings dominate the bimodal literature, while trimodal face-fingerprint-iris studies remain comparatively scarce. Feature-level fusion is reported less frequently than score-level fusion across the pool as a whole, consistent with its greater implementation difficulty, though the subset of feature-level studies shows a clear upward trend in the last three years, coinciding with wider adoption of convolutional feature extractors and metaheuristic feature selectors.

Consistent with the taxonomy in Section 2, the reviewed studies distribute across pre-mapping and post-mapping fusion. Deshmukh et al. (2013) fused face and fingerprint Gabor-filter features at the feature level, applying Linear Discriminant Analysis and Principal Component Analysis to control dimensionality, and reported a recognition accuracy of 99.25% against unimodal baselines. Bouzouina and Hamami (2017) fused face and iris features and used a Support Vector Machine for verification, achieving 98.8% accuracy. Veluchamy and Karlmarx (2017) fused finger-vein and knuckle features using a K-SVM classifier and achieved 96% accuracy. Alshebli et al. (2021) combined Discrete Wavelet Transform and Singular Value Decomposition for face-iris feature extraction and fusion, validating robustness on two public datasets. More recent work by Tyagi et al. (2025) proposes an optimized feature-level fusion framework for iris and fingerprint using machine-learning classifiers with augmentation strategies to address class imbalance, and a 2025 study by the same broad research community proposes a Bayesian-optimized SVM feature-fusion (BSFF) technique combining iris, fingerprint, and ear biometrics, reporting an average equal error rate of 0.1478 and accuracy of 0.9343 under five-fold cross-validation.

Score-level and decision-level fusion remain more common in the applied literature because they sidestep the dimensionality and heterogeneity problems inherent to feature-level fusion. Telgad et al. (2014) fused face and fingerprint match scores using a Euclidean-distance matcher; Dwivedi and Dey (2019) combined score-level fusion with cancellable biometric templates and Dempster-Shafer evidence theory, though without a systematic sensitivity analysis of the theory's underlying assumptions; and a 2022 study on smart-city authentication used an optimized fuzzy genetic algorithm for score-level fusion of fingerprint and iris. Sagar and Jain (2023) fused fingerprint and iris convolutional features at the score level, while a 2025 study on face-and-speech authentication used an improved Manta Ray Foraging Optimization algorithm for feature-level fusion, achieving accuracies of 98.23% and 97.92% on two public datasets with equal error rates near 3%, illustrating that bio-inspired metaheuristics continue to be actively explored for fusion optimization beyond BFOA specifically.

Within the immune-inspired family, Adedeji et al. (2019) applied the Clonal Selection Algorithm (CSA) to feature-level fusion of multimodal systems and reported improved recognition accuracy for bimodal configurations relative to their unimodal counterparts, while Adedeji et al. (2021) developed a Modified Clonal Selection Algorithm (MCSA) that replaced random tournament selection with a neighbourhood-based tournament to reduce between-group selection pressure, yielding higher accuracy and lower recognition time than standard CSA for face-iris-fingerprint fusion. Jooda et al. (2021) applied Artificial Bee Colony optimization to fingerprint feature selection, reporting 97.69% sensitivity and 96.76% recognition accuracy while substantially reducing feature-space dimensionality.

Within the swarm-intelligence family, an optimized hybrid framework combining Support Vector Machine and Random Forest classifiers with both BFO and Genetic Algorithm optimization was proposed for fingerprint, iris, and face fusion, using Gabor-filter feature extraction and feature-level fusion, and reported improved accuracy and robustness relative to single-classifier baselines. Vensila and Boyed (2024) applied an adjustable Particle Swarm Optimization variant to feature optimization for finger-vein, face, and fingerprint fusion ahead of classification with a broad learning machine. Soleymani et al. (2018) fused iris, face, and fingerprint features at multiple depths within a convolutional network using multi-abstract and weighted feature-fusion strategies, finding that trimodal fusion consistently outperformed bimodal and unimodal configurations. Al-Waisy et al. (2018) fused left- and right-iris features using ranking-level fusion within a convolutional pipeline (IrisConvNet) and reported a 100% recognition rate on their evaluation set, although generalization beyond the reported dataset was not established.

The reviewed BFOA-specific literature reflects three broad enhancement strategies pursued since Passino's (2002) original formulation: adaptive step-size control, modified swarming or hybridized search operators, and stochastic diversification mechanisms.

Adaptive step-size approaches address the single most frequently cited weakness of classical BFOA, its fixed chemotaxis step size, which forces a trade-off between fast early exploration and precise late-stage exploitation that a constant step cannot resolve. Zhang, Lv, and Zhou (2023) proposed a self-adaptive step-size equation for microgrid dispatch, combining it with a particle-swarm-style velocity update to improve convergence speed and precision. An enhanced BFO applying chaotic chemotaxis step length together with Gaussian mutation and chaotic local search (CCGBFO) was likewise shown to improve exploration-exploitation balance and shorten convergence time relative to classical BFOA on benchmark functions.

Hybridized and stochastic-diversification variants recur throughout the decade preceding this review. Tang et al. (2016) introduced new chemotaxis and conjugation strategies (BFO-CC), in which each bacterium selects a standard-basis-vector swimming direction and adapts its step size according to the evolutionary generation and the globally best individual, improving the exploration-exploitation balance and convergence speed. Wanga et al. (2018) proposed a bare-bones BFO (BBBFO) in which the chemotactic strategy draws on a Gaussian distribution informed by both individual history and group-shared information. Pang et al. (2019), and independently a related study using the same underlying mechanism, developed a Lévy-flight and PSO-operator hybrid (LPBFO) in which each bacterium tumbles along a single randomly selected dimension with a step size drawn from an adaptively shrinking Lévy-flight distribution, moving the population from global to local search as the run progresses. Liang and Tian (2017) hybridized BFO with PSO directly, allowing selective bacterial migration at a defined probability, and reported faster convergence and improved robustness over either parent algorithm alone. A comprehensive-swarm-learning variant incorporating cooperative communication with the global-best bacterium alongside competitive learning mechanisms has also been shown to improve convergence accuracy relative to earlier hybrids.

Two structural themes recur across nearly all of these variants and are directly relevant to feature-level biometric fusion. First, every reviewed enhancement targets either the chemotaxis step-size schedule or the tumbling-direction selection mechanism, confirming that this is the principal convergence bottleneck in classical BFOA. Second, elimination-dispersal, the mechanism most directly responsible for preventing premature convergence to a local optimum, receives comparatively little targeted attention in the literature relative to chemotaxis; most variants retain a fixed or only lightly modified elimination-dispersal probability even where the chemotaxis operator has been substantially redesigned. This asymmetry constitutes one of the clearest gaps identified by this review and is addressed directly in Section 6.

The most recent studies in the pool show three converging trends. The first is the pairing of deep convolutional feature extractors with metaheuristic feature selectors or classifiers, rather than relying on either mechanism alone, as seen in the CNN-Bayesian-optimized-SVM fusion of iris, fingerprint, and ear traits and in ResNet/VGGNet/DenseNet-based fingerprint-and-finger-vein fusion. The second is the continued exploration of alternative bio-inspired metaheuristics, such as Manta Ray Foraging Optimization for face-speech fusion, alongside BFOA, suggesting that the biometric-fusion community treats BFOA as one option within a broader, still-expanding swarm-intelligence toolkit rather than a settled default. The third is a persistent gap between the volume of general-purpose BFOA enhancement research and the comparatively small number of studies that apply an enhanced BFOA specifically at the feature level of a trimodal face-fingerprint-iris system, which is the gap this review positions its associated primary study to address.

Table 2. Summary of representative studies on feature-level fusion and BFOA-family optimization.

Study	Modalities	Fusion Level	Method	Reported Accuracy/Error
Deshmukh et al. (2013)	Face, Fingerprint	Feature	Gabor + LDA/PCA	99.25% accuracy
Tang et al. (2016)	Benchmark functions	N/A	BFO-CC (chemotaxis/conjugation)	Improved convergence vs. BFOA
Bouzouina & Hamami (2017)	Face, Iris	Feature	SVM classifier	98.8% accuracy
Veluchamy & Karlmarx (2017)	Finger vein, Knuckle	Feature	K-SVM	96% accuracy
Wanga et al. (2018)	Benchmark functions	N/A	Bare-bones BFO (BBBFO)	Improved exploration
Al-Waisy et al. (2018)	Left/Right Iris	Rank	IrisConvNet + CNN	100% recognition rate
Soleymani et al. (2018)	Iris, Face, Fingerprint	Feature (multi-depth)	CNN weighted fusion	Trimodal > bimodal/unimodal
Adedeji et al. (2019)	Face, Iris, Fingerprint	Feature	Clonal Selection Algorithm	Improved vs. unimodal
Pang et al. (2019)	Benchmark functions	N/A	Lévy-flight + PSO BFO (LPBFO)	Faster global-to-local transition
Alshebli et al. (2021)	Face, Iris	Feature	DWT + SVD	Robust across 2 datasets

Study	Modalities	Fusion Level	Method	Reported Accuracy/Error
Adedeji et al. (2021)	Face, Iris, Fingerprint	Feature	Modified CSA (MCSA)	Higher accuracy, lower time vs. CSA
Jooda et al. (2021)	Fingerprint	Feature selection	Artificial Bee Colony	96.76% accuracy
Zhang, Lv & Zhou (2023)	Microgrid dispatch	N/A	Adaptive-step BFO	Faster convergence, higher precision
Sagar & Jain (2023)	Fingerprint, Iris	Score	CNN feature extraction	Improved over unimodal
SVM-RF hybrid (2025)	Fingerprint, Iris, Face	Feature	SVM+RF, BFO/GA optimized	Improved accuracy/robustness
Tyagi et al. (2025)	Iris, Fingerprint	Feature	ML classifiers + augmentation	Threshold-tuned performance
Jha et al. (2025)	Face, Speech	Feature	Improved Manta Ray FO	98.23% / 97.92% accuracy
Vensila & Boyed (2024)	Finger vein, Face, Fingerprint	Feature	Adjustable PSO + broad learning	Reported strong outcomes

5. Towards an Enhanced BFOA for Feature-Level Fusion

Building on the gaps identified in the section above, this review outlines the design rationale for an Enhanced Bacteria Foraging Optimization Algorithm (EBFOA) intended for feature-level fusion of face, fingerprint, and iris traits, without presenting new experimental results, which belong to the associated primary study.

Rather than fixing the chemotaxis step size C(i) at a constant value for the entire run, an adaptive schedule assigns a larger step size to each bacterium during the early iterations to promote rapid exploration of the high-dimensional fused feature space, and progressively reduces the step size in later iterations to favour fine-grained exploitation around promising regions. This directly targets the convergence-speed weakness that recurs across the reviewed BFOA-enhancement literature and mirrors, in spirit, the adaptive and Lévy-flight step-size strategies reviewed above, while remaining tailored to the specific dimensionality profile of trimodal feature-level fusion.

Rather than the fixed elimination-dispersal probability Ped used in classical BFOA, a non-uniform probability distribution is applied across the population, increasing the likelihood of dispersal for bacteria that have stagnated in low-fitness regions while preserving high-performing bacteria at a lower dispersal probability. This is intended to reduce the risk of premature convergence and trapping in local optima that identified as comparatively under-addressed relative to chemotaxis-focused enhancements in the wider literature.

Applied to feature-level fusion of face, fingerprint, and iris features extracted via Discrete Wavelet Transform, the two modifications above are expected to improve the exploration-exploitation balance of the search, shorten convergence time relative to classical BFOA, and thereby reduce the computational overhead associated with feature-level fusion while maintaining or improving recognition accuracy across unimodal, bimodal, and multimodal modal configurations.

6. Discussion and Future Work

Read together, the reviewed studies indicate that feature-level fusion continues to be pursued because of its accuracy ceiling relative to score- and decision-level alternatives, even as most applied systems continue to default to score-level fusion for its comparative implementation simplicity. Metaheuristic optimization, and BFOA specifically, has matured considerably as a general-purpose search tool, with a decade of incremental chemotaxis and swarming refinements, yet its translation into trimodal biometric feature-level fusion specifically lags behind its maturity as an optimization technique in other domains such as energy dispatch and benchmark-function optimization. This mismatch is the central finding of the review and the primary justification for the EBFOA direction.

Several limitations of the review itself should be acknowledged. The heterogeneity of datasets, modalities, and reported metrics across the included studies precluded a quantitative meta-analysis, so the synthesis in above sections is necessarily narrative rather than statistical. The search was limited to English-language sources, which may exclude relevant work published in other languages.

Finally, because BFOA research spans engineering, computer science, and operations domains, some enhancement variants developed outside the biometrics literature but potentially transferable to it may not have surfaced in the biometric-focused search strings used here, despite the backward-snowballing step intended to mitigate this risk.

This review systematically examined 38 studies spanning feature-level fusion architectures in multibiometric systems and the evolution of BFOA-family metaheuristics. It found that while feature-level fusion is consistently associated with the highest reported accuracies among fusion strategies, its implementation difficulty, chiefly the curse of dimensionality and the unknown relationship between heterogeneous feature spaces, has limited its adoption relative to score-level fusion. It further found that BFOA enhancement research has concentrated heavily on the chemotaxis step-size and tumbling-direction mechanisms, with comparatively less attention to elimination-dispersal, and that the specific combination of feature-level fusion, multimodal face-fingerprint-iris configuration, and BFOA-family optimization remains under-explored. These findings motivate the Enhanced BFOA, which adapts the chemotaxis step size across iterations and applies a non-uniform elimination-dispersal probability.

Future primary research should evaluate such an enhanced algorithm against standard BFOA and other metaheuristics across matched unimodal, bimodal, and multimodal configurations using a common, ideally chimeric, dataset; report convergence behaviour explicitly alongside terminal accuracy, FAR, and FRR; and assess computational cost and real-time feasibility for deployment in access-control, financial, and law-enforcement contexts. Standardization of benchmark datasets and reporting metrics across the feature-level fusion literature would materially improve the comparability of future studies and is recommended as a priority for the research community.

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