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Half mirror algorithm: a metaheuristic that hybridizes swarm intelligence and evolution-based system

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ABSTRACT

This paper promotes a new metaheuristic called the half mirror algorithm (HMA). As its name suggests, HMA offers a new kind of mirroring search. HMA is developed by hybridizing swarm intelligence and the evolution system. Swarm intelligence is adopted by constructing several autonomous agents called swarms. On the other hand, the evolution system is adopted using arithmetic crossover based on a particular reference called a mirror. Four mirrors are used in HMA: the best swarm member, a randomly selected swarm member, the central point of the space, and the corresponding swarm member. During the confrontative assessment, HMA is confronted with average and subtraction-based optimization (ASBO), total interaction algorithm (TIA), walrus optimization algorithm (WaOA), coati optimization algorithm (COA), and clouded leopard optimization (CLO). The result shows that HMA is superior to ASBO, TIA, WaOA, COA, and CLO in 20, 19, 19, 20, and 20 out of 23 functions, respectively. Moreover, HMA has found the global optimal of eight functions. It means the superiority of HMA occurs in almost entire functions. In the future, the mirroring search can be combined with the guided and neighborhood search to construct a more powerful metaheuristic.

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1. INTRODUCTION

Metaheuristics plays a pivotal role in optimization, particularly in engineering studies. The application of metaheuristics as a primary tool for optimization is widespread across various engineering domains. A notable instance involves hybridizing the genetic algorithm (GA) and bacterial foraging optimization, which has proven effective in optimizing power grid stabilization within multi-machine environments [1]. Another innovative approach combines the capabilities of grey wolf optimization (GWO) and particle swarm optimization (PSO) to address path-planning challenges in mobile robot systems [2]. In power systems, the artificial bee colony (ABC) algorithm has been harnessed to enhance the location optimization of capacitor banks and distributed generators, focusing on improving reliability and diminishing power loss [3]. Meanwhile, the GA has demonstrated its prowess in optimizing packet routes within computer networks, aiming to minimize delay, hop count, and overall cost [4].

In the recent development of metaheuristics, swarm intelligence has become more dominant than the evolution-based system. Many recent metaheuristics are developed based on the swarm intelligence platform. Some of them imitate the animal behavior, such as Komodo mlipir algorithm (KMA) [5], clouded leopard optimization (CLO) [6], slime mold algorithm (SMA) [7], butterfly optimization algorithm (BOA) [8], golden jackal optimization (GJO) [9], northern goshawk optimization (NGO) [10], pelican optimization algorithm (POA) [11], marine predator algorithm (MPA) [12], coati optimization algorithm (COA) [13], zebra optimization algorithm (ZOA) [14], osprey optimization algorithm (OOA) [15], walrus optimization algorithm (WaOA) [16], white shark optimization (WSA) [17], Siberian tiger optimization (STO) [18], remora optimization algorithm (ROA) [19], Tasmanian devil optimization (TDO) [20], grey wolf optimization (GWO) [21], and so on. Some of them imitate the behavior of human mechanisms, such as modified social forces algorithm (MSFA) [22], driving training-based optimization (DTBO) [23], chef-based optimization algorithm (CBOA) [24], election-based optimization algorithm (EBOA) [25], mother optimization algorithm (MOA) [26], and so on. Some of them promote their fundamental strategy as their name rather than the use of metaphor, such as average subtraction-based optimization (ASBO) [27], total interaction algorithm (TIA) [28], attack-leave optimization (ALO) [29], golden search optimization (GSO) [30], and so on.

On the other hand, the evolution-based system is less prevalent. Nowadays, finding new evolution-based metaheuristics becomes more difficult. Some of them are the coronavirus optimization algorithm and the flower pollination algorithm. Ironically, the evolution-based metaheuristic was introduced earlier than the swarm intelligence. Moreover, the genetic algorithm, as the most popular evolution-based metaheuristic, is still utilized in many recent studies regarding optimization, such as for power system stabilizers [1], path planning [31], vehicular ad-hoc network [32], text encryption [33], vehicle scheduling [34], credit rating system [35], course timetabling [36], cloud system [37], and so on. This circumstance becomes the primary motivation of this work in developing a new evolution-based metaheuristic.

Based on this problem, this work aims to develop a new metaheuristic that hybridizes the swarm intelligence and crossover technique called half mirror algorithm (HMA). This hybridization is used for constructing a unique search technique called mirroring search. Four references are used as mirrors in HMA: the best swarm member, the randomly selected swarm member, the central point of the space, and the corresponding swarm member itself. Then, the performance of HMA is investigated through two assessments: the confrontative assessment and the individual search assessment. Based on this explanation, the innovation and contribution of this work is: i) This work offers the hybridization of swarm intelligence and arithmetic crossover called HMA, ii) This work proposes a new type of search called mirroring search, iii) The performance of HMA as a whole package is investigated through confrontative assessment, and iv) The contribution of each search constructing the HMA is investigated through the individual search assessment.

The rest of this paper is arranged as follows. Section 2 reviews the recent metaheuristic and more detailed justification of this work. Section 3 presents the method conducted in this work, consisting of the model and the assessment scenario. The description of the HMA, including its fundamental concept, is provided in detail. The assessment scenario comprises the use case, benchmark, and parameter setting. Section 4 consists of the assessment result and the more comprehensive investigation based on the outcome, drawback to the theory, limitation, complexity, and the proposal for future development. Finally, section 5 consists of the conclusion and the summarized future work.

2. RELATED WORKS

Evolution-based metaheuristics were developed long ago and are still widely used today. The evolution-based metaheuristic is a frog-leap innovation because it adopts a population-based system where the metaheuristic system consists of a set of solutions [38]. It differs from the earlier metaheuristic version that assumes a single agent-based system, which appears in tabu search, simulated annealing, and variable neighborhood search.

The fundamental concept of the evolution-based system is generating a new generation through the crossover mechanism of selected parents [38]. In this process, the selection of the parents becomes the critical aspect for improvement. The most common parent selection is based on a roulette wheel. Through the roulette wheel, all current solutions can be selected as parents to produce new solutions [39]. However, each solution's probability of being chosen as a parent varies relative to others. Through normalized comparison of their quality, a solution whose quality is better will have a better chance of being selected. It makes the probability of producing a better solution will be higher. Meanwhile, allowing the inferior ones to be chosen still opens the improvement through inadequate parents. The rationale can be traced to the nature of the stochastic method, which cannot guarantee finding the global optimal solution. Focusing only on the superior solution may drive to the local optimal solution.

As time passes, swam intelligence takes over the dominance of the evolution-based system. Swarm intelligence is also a population-based method. But, in swarm intelligence, all solutions become active autonomous agents so that, in general, through many experiments, swarm-based metaheuristics can find better results than evolution-based metaheuristics. From a different point of view, the swarm-based metaheuristic is faster than the evolution-based metaheuristic.

The superiority of swarm intelligence also comes from the massive interaction among swarm members. Various references can be chosen as interaction partners, such as the global best, local best, the best swarm member among the population, another member, a randomly picked better member, a randomly picked worse member, or the resultant of better members. In some swarm intelligence, the reference can be the middle between the best solution so far to the current iteration and the best solution among the population in the current solution as implemented in crayfish optimization algorithm [40]. Meanwhile, in prairie dog optimization (PDO), there are four equal size stages from the first iteration to the maximum iteration where there is distinct reference in every phase [41]. The direction of the motion during the guided search can be moving toward or away from the reference. The step size can be uniform, which is commonly found in many swarm-based metaheuristics such as in POA [11], NGO [10], TIA [28], ASBO [27], and so on, levy flight or Brownian motion as in MPA [12], or normal distribution as in KMA [5]. Some metaheuristics apply division roles where some swarm members run specific strategies while others run another approach, like in COA [13], and KMA [5]. Meanwhile, some metaheuristics do not apply division of roles so that all swarm members run the same strategy.

In recent years, the adoption of multiple search approaches has become common. The rationale is that each strategy has its strengths and weaknesses, and there is not any superior strategy that is the best to solve all kinds of problems, as stated in the no-free-lunch (NFL) theory. This circumstance also motivates this work to create a new type of mirroring search. This search is the hybridization of the swarm intelligence and crossover method. This work also introduces the center of the space as a reference, which is uncommon and rare in many existing metaheuristics.

3. METHOD

3.1. Model

The fundamental concept of HMA is the hybridization of swarm intelligence and evolution-based systems. As a swam intelligence, HMA consists of several autonomous agents. As an evolution-based system, HMA utilized crossover as its core strategy in finding the optimal solution. In this work, an arithmetic crossover is chosen. Both concepts are used to create a new search strategy called mirroring search. In the mirroring search, a mirror is used as a reference to create a reflection entity called shadow. It means that the distance of the shadow to the mirror is equal to the length of the actual entity to the mirror. However, the location of the shadow is in the opposite direction of the real entity in the search space. The motivation is to ensure other regions within the distance are traced, too. As swarm intelligence, all swarm members perform mirroring searches. Meanwhile, as an evolution-based system, this search produces seeds. There are two seeds planted in the mirroring search. The first seed is right in the middle between the actual entity and the mirror. On the other hand, the second seed is right in the middle between the shadow and the mirror or the actual entity. Then, both seeds are confronted, and the better seed becomes the candidate for replacement.

There are four references or mirrors used in HMA. It means that each swarm member performs four mirroring searches in every iteration. These mirrors are the best swarm member, the randomly selected swarm member, the central point of the space, and the swarm member itself. These four searches are visualized in Figure 1. Then, this fundamental concept is formalized using pseudocode and mathematical formulation. The annotations used in this paper are as follows: d is dimension; f is objective function; i, j are index for swarm members, index for dimension; S is swarm; s is swarm member; s_b is best swarm member; s_c is the best seed; s_{lo}, s_{hi} are the lower boundary of search space, the higher boundary of space; s_{se1}, s_{se2} are first seed, second seed; $s_{sh1}, \ldots, s_{sh4}$ are first to the fourth shadow; t is iteration; and t_m is maximum iteration.

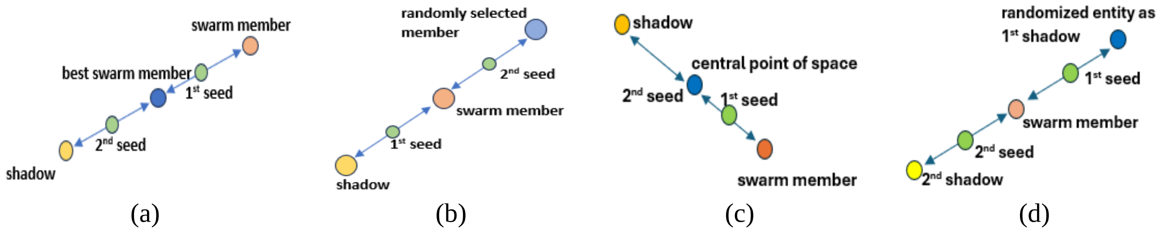

Figure 1. Visualization of half mirror algorithm: (a) first mirror search, (b) second mirror search, (c) third mirror search, and (d) fourth mirror search

As a swarm intelligence, HMA consists of a collection of swarm members. It is formulated using (1). Then, in the initialization phase, all swarm members are generated uniformly within the search space as formulated using (2). The objective is to provide equal opportunity in the search space to be selected as the initial solution.

$$S = \{s_1, s_2, s_3, \dots, s_n\} \tag{1}$$

$$s_{i,j} = s_{lo,j} + U(0,1).(s_{hi,j} - s_{lo,j}) \tag{2}$$

The strict acceptance rule is used in HMA and formulated using (3) to (5). Equation (3) is utilized to select the best seed. Equation (4) is utilized to update the current swarm member. Equation (5) is utilized to update the best swarm member.

$$s_c = \begin{cases} s_{se1}, f(s_{se1}) < f(s_{se2}) \\ s_{se2}, else \end{cases} \tag{3}$$

$$s_i' = \begin{cases} s_i, f(s_c) < f(s_i) \\ s_i, else \end{cases} \tag{4}$$

$$s_b' = \begin{cases} s_i, f(s_i) < f(s_b) \\ s_b, else \end{cases} \tag{5}$$

The first mirroring search is formulated using (6) to (8). Equation (6) determines the shadow of the first mirror based on the best swarm member. Equations (7) and (8) determine the first and second seeds. The first seed is right between the best and best swarm members. The second seed is right between the swarm member and the shadow of the first mirror.

$$s_{sh1,j} = s_{i,j} + 2\left(s_{b,j} - s_{i,j}\right) \tag{6}$$

$$s_{se1,j} = \frac{s_{i,j}+s_{b,j}}{2} \tag{7}$$

$$s_{se2,j} = \frac{s_{i,j}+s_{sh1,j}}{2} \tag{8}$$

The second mirroring search is formulated using (9) to (12). Equation (9) determines a randomly selected swarm member as the mirror while (10) is used to determine the shadow. Equations (11) and (12) are used to determine the seeds.

$$s_{rs} = U(S) \tag{9}$$

$$s_{sh2,j} = 2s_{i,j} - s_{rs,j} \tag{10}$$

$$s_{se1,j} = \frac{s_{i,j}+s_{rs,j}}{2} \tag{11}$$

$$s_{se2,j} = \frac{s_{i,j}+s_{sh2,j}}{2} \tag{12}$$

The third mirroring search is formulated using (13) to (16). Equation (13) determines the central point of the space as the mirror. Equation (14) is used to determine the shadow. Then, (15) and (16) are used to determine the first and second seeds. The first seed is the middle between the actual entity and the mirror as presented in (15). The second seed is the middle between the actual entity and the shadow as presented in (16).

$$s_{c,j} = \frac{s_{lo,j}+s_{hi,j}}{2} \tag{13}$$

$$s_{sh3,j} = 2s_{c,j} - s_{i,j} \tag{14}$$

$$s_{se1,j} = \frac{s_{i,j}+s_{c,j}}{2} \tag{15}$$

$$s_{se2,j} = \frac{s_{i,j}+s_{sh3,j}}{2} \tag{16}$$

The fourth mirroring search is formulated using (17) to (20). Equation (17) is used to determine the first shadow while (18) is used to determine the second shadow. Equation (19) states that the first seed is in the middle between the actual entity and the first shadow. Equation (20) states that the second seed is in the middle between the actual entity and the second shadow.

$$s_{sh41,j} = s_{i,j} + \frac{s_{lo,j}+U(0,1).(s_{hi,j}-s_{lo,j})}{t} \tag{17}$$

$$s_{sh42,j} = 2s_{i,j} - s_{sh41,j} \tag{18}$$

$$s_{se1,j} = \frac{s_{i,j}+s_{sh41,j}}{2} \tag{19}$$

$$s_{se2,j} = \frac{s_{i,j}+s_{sh42,j}}{2} \tag{20}$$

Formalization of all processes in HMA is presented through pseudocode and flowchart. The pseudocode of HMS is presented in Algorithm 1. Meanwhile, the flowchart of HMA is presented in Figure 2.

Algorithm 1. Half mirror algorithm
```
begin
  for i=1 to n(S)
    initialize si using (1)
    update sb using (2)
  end for
  for t=1 to tm
    for i=1 to n(S)
      first mirroring search using (6)-(8) and (3)-(5)
      second mirroring search using (9)-(12) and (3)-(5)
      third mirroring search using (13)-(16) and (3)-(5)
      fourth mirroring search using (17)-(20) and (3)-(5)
      update sb using (2)
    end for
  end for
  return sb
end
```

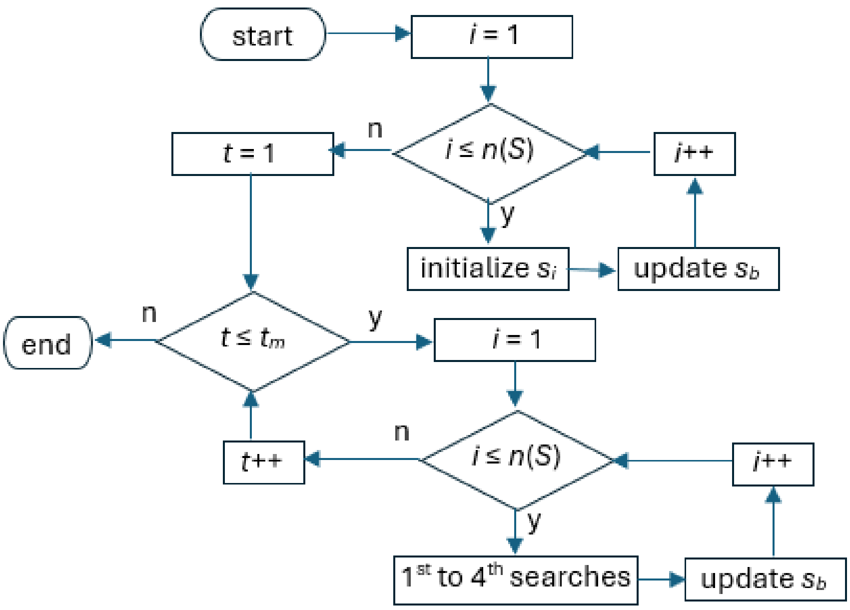

Figure 2. Flowchart of half mirror algorithm

3.2. Assessment procedure

There are two assessments carried out in this work. The first assessment is the confrontative assessment. The second assessment is the individual search assessment. HMA is confronted with five other metaheuristics developed based on swarm intelligence in the confrontative assessment. The objective of the confrontative assessment is to investigate the comparative advantage of HMA relative to its confronters. This assessment investigates HMA as a whole package of optimization techniques. On the other hand, the objective of the individual search assessment is to investigate the contribution of each search in constructing the HMA. In the era of multiple search metaheuristic, it is crucial to investigate the contribution of each search in the related metaheuristic besides the whole package of this metaheuristic as in the first assessment. The individual search assessment is also essential for future development to discriminate which searches are prospective to be used or improved in future development and which searches are not prospective enough.

In both assessments, a set of 23 functions is used as the use case. There are two rationales for using this set of functions as a use case for this work. The first rationale is that it covers various circumstances of the optimization process. It consists of seven high-dimension unimodal functions (HUF), six high-dimension multimodal functions (HMF), and ten fixed-dimension multimodal functions (FMF). The detailed description of these functions is exhibited in Table 1. Besides the dimension and the modality, there are various range spaces in this set of functions. Some functions have a considerable range of space, such as Schwefel and Griewank. On the other hand, some functions have very narrow range space, such as Quartic and Hartman. In some functions, the global optimal solution lies in or near the center of space. On the other hand, in some functions, their global optimal solution is far from the center of the space. Some functions have curvy terrain, while others have flat terrain with a narrow hole where the global optimal solution exists.

Table 1. Benchmark functions

No	Function	Type	Dim	Range Space	Target
F1	Sphere	HUF	55	[-100, 100]	0
F2	Schwefel 2.22	HUF	55	[-100, 100]	0
F3	Schwefel 1.2	HUF	55	[-100, 100]	0
F4	Schwefel 2.21	HUF	55	[-100, 100]	0
F5	Rosenbrock	HUF	55	[-30, 30]	0
F6	Step	HUF	55	[-100, 100]	0
F7	Quartic	HUF	55	[-1.28, 1.28]	0
F8	Schwefel	HMF	55	[-500, 500]	-418.9 x *dim*
F9	Ratsrigin	HMF	55	[-5.12, 5.12]	0
F10	Ackley	HMF	55	[-32, 32]	0
F11	Griewank	HMF	55	[-600, 600]	0
F12	Penalized	HMF	55	[-50, 50]	0
F13	Penalized 2	HMF	55	[-50, 50]	0
F14	Shekel Foxholes	FMF	2	[-65, 65]	1
F15	Kowalik	FMF	4	[-5, 5]	0.0003
F16	Six Hump Camel	FMF	2	[-5, 5]	-1.0316
F17	Branin	FMF	2	[-5, 5]	0.398
F18	Goldstein-Price	FMF	2	[-2, 2]	3
F19	Hartman 3	FMF	3	[1, 3]	-3.86
F20	Hartman 6	FMF	6	[0, 1]	-3.32
F21	Shekel 5	FMF	4	[0, 10]	-10.1532
F22	Shekel 7	FMF	4	[0, 10]	-10.4028
F23	Shekel 10	FMF	4	[0, 10]	-10.5363

In the confrontative assessment, five metaheuristics are selected as the confronters. They are ASBO, TIA, WaOA, COA, and CLO. All of them are swarm-based metaheuristics and new. Three of them (CLO and ASBO) were first introduced in 2022. Meanwhile, the three others (TIA, WaOA, and COA) were introduced in 2023. All of them implement a strict acceptance approach. TIA is the only metaheuristic consisting of only a single search. TIA and ASBO are metaheuristics that do not implement neighborhood search. All these metaheuristics do not have other adjusted parameters except the swarm size and maximum iteration. In the first assessment, the swarm size is set to 5 while the maximum iteration is set to 10.

There is only one active search in an assessment session in the individual search assessment. When a search is activated, the other searches are deactivated. Since four searches are constructing the HMA, four individual searches are assessed in every function. In this second assessment, the swarm size is also set to 5, and the maximum iteration is set to 10.

4. RESULTS AND DISCUSSION
4.1. Assessment result

The assessment result is presented in Tables 2 to 6. Table 2 to 4 present the result of the confrontative assessment regarding HUF, HMF, and FMF consecutively. Then, this result is summarized in Table 5 to investigate the superiority of the HMA related to its confronters. The result of the individual search assessment is presented in Table 6. The result is measured based on the fitness score for each function. Three parameters are observed in Tables 2 to 4: the mean, standard deviation, and the mean rank. In Table 6, the only parameter is the average fitness score, and the best result for each function is written in bold font. The decimal point smaller than 10^{-4} is rounded to the nearest decimal.

Table 2. Assessment results for the HUF

F	Parameter	ASBO	TIA	WaOA	COA	CLO	HMA
1	mean	7.2464×10^{2}	4.5701×10^{1}	6.5078×10^{1}	9.8303×10^{2}	1.8709×10^{3}	0.0000
	std deviation	1.4972×10^{2}	1.0249×10^{1}	8.7511×10^{1}	4.3792×10^{2}	9.1193×10^{2}	0.0000
	mean rank	4	2	3	5	6	1
2	mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	std deviation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	mean rank	1	1	1	1	1	1
3	mean	4.6975×10^{4}	1.5040×10^{4}	7.0641×10^{3}	4.1156×10^{4}	8.0928×10^{4}	0.0000
	std deviation	3.3146×10^{4}	1.6104×10^{4}	4.8350×10^{3}	2.5291×10^{4}	5.6698×10^{4}	0.0000
	mean rank	5	3	2	4	6	`1
4	mean	2.3017×10^{1}	4.5879	6.1943	2.6055×10^{1}	4.4620×10^{1}	0.0000
	std deviation	1.7761×10^{1}	1.3876	2.5867	7.1030	1.7124×10^{1}	0.0000
	mean rank	4	3	2	5	6	1
5	mean	5.2025×10^{4}	1.0174×10^{3}	1.1035×10^{3}	1.7622×10^{5}	5.8852×10^{3}	5.4000×10^{1}
	std deviation	2.1504×10^{4}	5.7064×10^{2}	1.1055×10^{3}	1.4627×10^{5}	8.3026×10^{4}	0.0000
	mean rank	5	2	3	6	4	1
6	mean	7.8692×10^{2}	4.9270×10^{1}	6.3545×10^{1}	1.0039×10^{3}	2.4401×10^{3}	1.3500×10^{1}
	std deviation	2.1504×10^{2}	1.6172×10^{1}	3.0286×10^{1}	3.6316×10^{2}	1.2410×10^{3}	0.0000
	mean rank	4	2	3	5	6	1
7	mean	0.2951	0.1063	0.0822	0.3642	0.7877	0.0033
	std deviation	0.1164	0.0848	0.0409	0.1951	0.3333	0.0028
	mean rank	4	3	2	5	6	1

Table 3. Assessment result for the HMF

F	Parameter	ASBO	TIA	WaOA	COA	CLO	HMA
8	mean	-3.7662×10^{3}	-2.2313×10^{3}	-3.5721×10^{3}	-3.8711×10^{3}	-3.7077×10^{3}	-5.2129×10^{3}
	std deviation	4.1503×10^{2}	6.4302×10^{2}	6.4205×10^{2}	6.6288×10^{2}	5.0373×10^{2}	1.0232×10^{3}
	mean rank	3	6	5	2	4	1
9	mean	3.6956×10^{1}	1.0238×10^{2}	7.9652×10^{1}	1.7395×10^{2}	3.5568×10^{2}	0.0000
	std deviation	1.0210×10^{1}	7.3754×10^{1}	4.3545×10^{1}	4.6774×10^{1}	6.8749×10^{1}	0.0000
	mean rank	2	4	3	5	6	1
10	mean	7.2519	2.2282	2.2600	6.3446	8.6804	0.0000
	std deviation	1.7004	0.2361	0.4986	0.9821	1.7602	0.0000
	mean rank	5	2	3	4	6	1
11	mean	7.2866	1.4123	1.3948	1.1496×10^{1}	2.0200×10^{1}	0.0000
	std deviation	2.0419	0.1156	0.2944	3.8984	1.0107×10^{1}	0.0000
	mean rank	4	3	2	5	6	1
12	mean	6.1465	1.3342	1.5079	8.0613×10^{1}	9.3394×10^{3}	1.4401
	std deviation	2.4322	0.2653	0.3513	2.6728×10^{2}	2.6129×10^{4}	0.0000
	mean rank	4	1	3	5	6	2
13	mean	3.6482×10^{3}	5.4224	5.1987	2.6047×10^{4}	7.7354×10^{5}	3.1400
	std deviation	4.4949×10^{3}	1.1491	0.8411	4.5040×10^{4}	1.8269×10^{6}	0.0000
	mean rank	4	3	2	5	6	1

The result in Table 2 indicates the general superiority of HMA among its confronters. HMA is placed on the first rank for all high-dimensional unimodal functions. Meanwhile, all metaheuristics in this work achieve the same result in solving f_2. Moreover, HMA can find the global optimal solution in solving four functions (f_1, f_2, f_3, and f_4). WaOA becomes the second-best performer, while TIA becomes the third-best performer in solving HUFs. Meanwhile, the CLO becomes the worst performer in solving HUFs. The performance gap between HMA as the best performer and CLO as the worst performer is wide except in solving f_2.

Result in Table 3 still indicates the superiority of HMA among its confronters in solving the high-dimension multimodal functions. HMA is placed on the first rank in five out of six functions (f_8, f_9, f_{10}, f_{11}, and f_{13}). It also achieves the global optimal solution in three functions (f_9, f_{10}, and f_{11}). HMA has become the second-best performer in solving f_{12}. In this second group, the performance gap between the best and worst performers is wide in three functions (f_9, f_{12}, and f_{13}). Meanwhile, the performance gap in f_8 is narrow.

The result in Table 4 exhibits the close confrontation among the metaheuristics in solving the fixed dimension multimodal functions. The performance gap among metaheuristics is narrow and it happens in all ten functions. In these functions, HMA is as still superior as in the first and second groups of functions. In this group, HMA is eight times in the first rank (f_{16} to f_{23}). HMA is in the third rank in f_{15} and fifth rank in f_{14}.

Table 4. Assessment result for the FMF

F	Parameter	ASBO	TIA	WaOA	COA	CLO	HMA
14	mean	8.1266	1.9256×10^1	9.9753	7.8946	9.3120	1.0649×10^1
	std deviation	5.2051	2.2925×10^1	4.4421	5.4138	4.4474	3.2901
	mean rank	2	6	4	1	3	5
15	mean	0.1225	0.0084	0.0076	0.0133	0.0143	0.0109
	std deviation	0.0340	0.0101	0.0105	0.0114	0.0092	0.0182
	mean rank	6	2	1	4	5	3
16	mean	-0.0104	-1.0066	-1.0249	-1.0117	-1.0066	-1.0313
	std deviation	0.0465	0.0482	0.0105	0.0303	0.0505	0.0006
	mean rank	4	5	2	3	5	1
17	mean	1.6489	2.5087	0.4039	0.4572	0.4917	0.3981
	std deviation	1.8918	4.2181	0.0100	0.0868	0.1667	0.0000
	mean rank	5	6	2	3	4	1
18	mean	1.5500×10^1	4.2059×10^1	1.6775×10^1	1.5756×10^1	1.5369×10^1	4.2336
	std deviation	5.7282×10^1	5.3512×10^1	2.2696×10^1	2.0131×10^1	1.8294×10^1	5.6227
	mean rank	3	6	5	4	2	1
19	mean	-0.0495	-0.0495	-0.0495	-0.0495	-0.0495	-0.0495
	std deviation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	mean rank	1	1	1	1	1	1
20	mean	-0.6235	-2.1222	-2.8007	-2.8208	-2.6607	-3.1826
	std deviation	0.4369	0.4413	0.1718	0.2626	0.3477	0.0807
	mean rank	6	5	3	2	4	1
21	mean	-2.4067	-1.6822	-1.3290	-1.9384	-2.3376	-3.1826
	std deviation	2.9488	1.0068	0.6841	1.0032	-0.7993	0.0807
	mean rank	2	5	6	4	3	1
22	mean	-2.0810	-1.6276	-2.0925	-1.9787	-2.0706	-4.6168
	std deviation	1.9126	0.9683	1.2534	0.9524	0.7951	2.2244
	mean rank	3	6	2	5	4	1
23	mean	-1.9984	-1.6735	-2.0933	-2.4510	-2.4997	-5.2445
	std deviation	2.1540	0.7053	1.1729	0.8752	1.0932	2.7444
	mean rank	5	6	4	3	2	1

The summarization presented in Table 5 strengthens the superiority of HMA in solving all groups of functions. Its superiority occurs whether they are high dimension unimodal functions, high dimension multimodal functions, and fixed dimension multimodal functions. HMA is superior to ASBO, TIA, WaOA, COA, and CLO in 20, 19, 19, 20, and 20 functions.

Table 5. Superiority assessment result based on the group of functions

Cluster	Number of Functions Beaten by HMA				
	ASBO	TIA	WaOA	COA	CLO
1	6	6	6	6	6
2	6	5	6	6	6
3	8	8	7	8	8
Total	20	19	19	20	20

The result in Table 6 exposes the fierce competition among these four searches in almost all functions. The performance gap between the best search and the worst search is narrow in almost all functions. The third search performs as the best search among these four searches as its superiority in twelve functions: eight high dimension functions and four fixed dimension functions. The first and third searches achieve the same result in solving f_2. Meanwhile, the first, third, and fourth searches achieve the same result in solving f_{19}.

Table 6. Assessment results regarding the individual search

Function	Average Fitness Score			
	1st search	2nd search	3rd search	4th search
1	1.5967×10^5	1.5833×10^5	**1.5818×10^5**	1.6389×10^5
2	**0.0000**	2.9382×10^{82}	**0.0000**	4.3836×10^{78}
3	1.1479×10^6	1.0500×10^6	**1.0323×10^6**	1.2816×10^6
4	9.7905×10^1	9.7091×10^1	**9.6818×10^1**	9.7619×10^1
5	7.8126×10^8	7.2368×10^8	**6.9275×10^8**	7.1462×10^8
6	1.5915×10^5	1.5827×10^5	1.6291×10^5	**1.5597×10^5**
7	6.7409×10^2	6.7751×10^2	6.9641×10^2	**6.6381×10^2**
8	**-1.9164×10^3**	-1.6244×10^3	-1.6819×10^3	-1.4304×10^3
9	9.4911×10^2	9.4384×10^2	**9.3749×10^2**	9.4196×10^2
10	2.1038×10^1	**2.1005×10^1**	2.1052×10^1	2.1042×10^1
11	1.4673×10^3	1.4690×10^3	**1.3956×10^3**	1.4608×10^3
12	**1.7158×10^9**	1.7570×10^9	1.7337×10^9	1.7338×10^9
13	3.4012×10^9	3.4039×10^9	**3.3307×10^9**	3.3585×10^9
14	4.4503×10^2	4.1059×10^2	**3.5360×10^2**	3.5475×10^2
15	2.5072	7.3910	**2.2058**	4.0929
16	8.1918×10^1	7.2865×10^1	**2.1096×10^1**	1.0348×10^2
17	1.1658×10^1	9.1033	2.0886×10^1	**7.3514**
18	**4.4918×10^2**	1.1558×10^3	1.2832×10^3	1.2288×10^3
19	**-0.0003**	0.0000	**-0.0003**	**-0.0003**
20	-0.6978	-0.5699	-0.7802	**-0.7914**
21	-0.3298	**-0.3390**	-0.2415	-0.2412
22	-0.4661	**-0.4957**	-0.3849	-0.3656
23	-0.5394	-0.5115	-0.4476	**-0.5927**

4.2. Discussion

In general, this study investigates the performance of the proposed algorithm in a more comprehensive way. Rather than investigates the proposed algorithm in a single package on solving the related problem which is commonly found in most of studies proposing new metaheuristic, this study also investigates the contribution of each search in helping the proposed HMA to solve the problem. Meanwhile, this study also investigates the computational complexity of HMA and all its contenders, strength and weakness, the limitations of the proposed HMA in a more detailed manner, and possible areas for further work.

The main finding of this study is that the mirroring-based search can compete with the guided search, which becomes the backbone of the swarm-based metaheuristic. This finding can be traced from the result of the confrontative assessment. This circumstance can be used for the indication related to the strength of the evolution-based metaheuristic to the swarm-based metaheuristic. As mentioned, swarm intelligence becomes more dominant than the evolution-based approach as a baseline for developing a recent metaheuristic. The result also indicates the competitiveness of the central point of the space as a reference compared to the best swarm member. Among the confronters, WaOA is the only metaheuristic that explicitly performs the guided search toward the best member in every iteration for all swarm members [16]. In this context, the best swarm member is the reference. The result of the confrontative assessment also shows that the fixed step size, like the halfway motion, is competitive rather than the uniform random-based step size performed by all confronters.

The computational time of the metaheuristics can be investigated through the analysis of their computational complexity. The computational complexity of the HMA is related to the number of loops that appeared in the algorithm. Based on this, there are differences regarding the complexity between the initialization phase and iteration phase. The computational complexity can be presented as $O(n(S).d)$ during the initialization phase. This presentation can be obtained because a nested loop consists of two loops during the initialization phase. The outer loop is for all swarm members, while the inner loop is for all dimensions. On the other hand, during the iteration phase, the computational complexity can be presented as $O(4t_m.n(S).d)$. This is because the nested loop in the iteration phase also consists of the loop until the maximum iteration. Meanwhile, four searches are performed in every iteration by each swarm member.

The computational complexity of HMA during the iteration phase is higher than ASBO, WaOA, COA, and CLO but tends to be lower than TIA. The complexity of TIA during iteration is presented as $O(t_m^2.n(S).d)$ as each swarm member interacts with all other members in every iteration [28]. In ASBO [27] and WaOA [16], the computational complexity is $O(3t_m.n(S).d)$ as each swarm member performs three sequential steps in every iteration in these metaheuristics. Meanwhile, In COA [13] and CLO [6], the computational complexity is $O(2t_m.n(S).d)$ as each swarm member performs two sequential steps in every iteration in these metaheuristics.

The complexity of HMA is less consuming than other metaheuristics that perform a sorting mechanism at the beginning of every iteration. Examples of these metaheuristics are KMA [5], GJO [9], GWO [21], and so on. In KMA, this sorting is needed to split the swarm members into three groups: the superior, moderate, and inferior [5]. In GJO, sorting is needed to find the two best swarm members that will move toward or away from the swarm members [9]. Meanwhile, in GWO, sorting is needed to determine the three best swarm members where their resultant becomes the reference for all swarm members [21].

Another note regarding the sorting process is the mechanism for handling worse or worse solutions. This mechanism is implemented in several metaheuristics. In GSO, a randomly selected swarm member replaces the worst swarm member [30]. In KMA, the inferior swarm members follow the resultant of the superior ones [5]. Meanwhile, many other techniques can be used to handle these members. But the more philosophical question is the necessity of the segregation of roles among the swarm members based on their performance or quality.

The mirroring search based on the central point of the search space becomes the source of strength in solving the high-dimension functions. This search pushes the swarm members toward the central point of the space because the result of this search is always the halfway point from the previous one. This search has proven effective in solving functions where the global optimal solution lies on or near the central point of the space, as found in many high-dimension functions except the Schwefel. Meanwhile, the theoretical weakness of mirroring search to solve the functions where the global optimal solution is far from the central point of the search space is tackled by the other searches.

There are limitations in HMA despite its superior performance. The first limitation is related to the NFL theory. HMA is not in the first rank in some functions, such as f_{12}, f_{14}, and f_{15}. All these three functions are multimodal functions. The second limitation is related to the strict acceptance approach. This approach is implemented in all metaheuristics in this assessment. The strict acceptance approach prevents the swarm members from approaching the worst solution. That is why only better solutions are approved as replacements for the existing solution by this approach. Unfortunately, this approach may be counterproductive in solving problems or functions where the terrain is flat in a large portion of the space. This circumstance makes the motion toward the global optimal solution harder to perform because the swarm members will face stagnation for specific times. However, this new solution is the right way toward the area of the global optimal solution.

This study demonstrated that the existence of central point of the search space can be combined with other mirrors to generate new hybrid mirrors in future studies. In HMA, the other mirrors are the best swarm members, a randomly selected swarm member, and a random generated entity within space. For example, a new mirror can be generated between the central point of the space and the best swarm member. This new mirror can be right in the middle between these two entities or anywhere between them. The hybridization can also be conducted among the central point, one of other three mirrors in HMA, the swarm member itself. The performance of other distributions, such as normal distribution, Brownian motion, or Levy flight, which is more complicated, should be further investigated. These distributions can be found in several metaheuristics, such as KMA [5], MPA [12], or PDO [41]. It also becomes the prospect of future studies by confronting HMA with these metaheuristics.

This recent observation has shown that the proposed HMA provides acceptable performance in solving quasi-optimal solutions. The result also shows that HMA is superior compared to its contenders. Besides, the complexity of HMA is also competitive as it does not perform sorting process before conducting the searching process. Meanwhile, as a metaheuristic, HMA still has limitations due to several reasons, such as the strict acceptance approach and its behavior to converge in the center of the space. Nevertheless, this observation has proposed the hybridization of central point with other entities as alternative reference and the use of various distribution for future studies.

5. CONCLUSION

This work's innovation and novel contribution mainly introduce a new stochastic optimization method called half mirror algorithm (HMA). It combines the fundamental concept of swarm intelligence and the arithmetic crossover technique. Through assessment, HMA can find an acceptable solution in solving the optimization use case where, in this work, the use case is a set of 23 functions. HMA is also superior to its confronters. Through assessment, HMA is better than ASBO, TIA, WaOA, COA, and CLO in 20, 19, 19, 20, and 20 functions, respectively. HMA has found the global optimal of eight functions. This distinct superiority of the HMA primarily comes in both high-dimensional functions and fixed dimension functions. Meanwhile, a fierce confrontation occurs in the fixed dimension multimodal functions. Through individual assessment, mirroring, where the reflector is the space's central point, plays the dominant role. This search can be challenged or combined with the guided search toward the best swarm member, commonly used in many swarm-based metaheuristics. Through the computational complexity analysis, the complexity of HMA is higher than ASBO, WaOA, COA, and CLO but tends to be lower than TIA.

In the future, this study can be further expanded or developed through several tracks. The first track combines the mirroring search with the guided or neighborhood search. The second track is implementing HMA in many practical use cases. The third track combines HMA as a metaheuristic technique with other deterministic techniques to solve bigger or more complex problems. The fourth track combines the central point of the space with other references to generate a new mirror.

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