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Multi-Lingual Entity Alignment with Hybrid Differential Evolution Algorithm

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Abstract. *The growing prevalence of entities described in multiple languages underscores the importance of achieving cross-language interoperability. To address the semantic disparities inherent in multi-lingual data, the task of identifying correspondences between heterogeneous entities, known as multi-lingual entity alignment, becomes crucial. However, due to the intricate challenges posed by semantic disparities across languages and the complexities involved in aligning entities described in different linguistic contexts, multi-lingual entity alignment remains a significant open challenge. To tackle this challenge, we propose a novel Hybrid Differential Evolution (HDE) algorithm to efficiently determine multi-lingual entity mappings. First, a novel multi-lingual similarity measure designed to comprehensively integrate the syntax and linguistic information of diverse entities, thereby enhancing its discriminative power. Then, a problem-specific HDE that incorporates a novel encoding mechanism to facilitate the search for optimal entity mapping sets. In addition, a new local search strategy employing multiple mutation strategies is presented to help the algorithm escape local optima. The experimentation utilizes the Multi-farm dataset provided by OAEI to evaluate the performance of the HDE approach. The results indicate that HDE substantially surpasses current leading multi-lingual entity matching methods, demonstrating its capability to bridge semantic gaps across diverse multi-lingual entities.*
Keywords: Multi-lingual Entity Alignment , Multi-lingual Similarity Measure , Differential Evolution Algorithm , Local Search Strategy

1. **Introduction.** With the increase in entities described in various languages, the importance of multi-lingual information is increasingly evident [1]. This is particularly the case as the number of content creators working in non-English languages expands, along with the evident need for cross-language interoperability [2]. To address the semantic disparities inherent in multi-lingual data, the identification of correspondences between heterogeneous entities becomes imperative, the so-called multi-lingual entity alignment

[3]. The goal of multi-lingual entity alignment is to establish mappings between entities expressed in different languages. An optimal model seeks to maximize the objective function $F(X)$ while satisfying constraints defined by the mapping set X:

- X represents a decision variable, which is a vector containing entity mappings. Each element x_i in X corresponds to the mapping of the i-th entity from the initial entity set E_1 to another entity in the second set E_2.
- The objective function $F(X)$ evaluates the quality of the entity alignment described by X. It calculates the ratio of the product of the number of mappings in A (the entity alignment) and the sum of similarity scores, to the product of the sizes of E_1 and E_2, multiplied by the total of mappings and similarity scores. This ratio is bounded between 0 and 1.

Due to the complexity of semantics between entities brought by different languages and the large number of entities, the problem of multi-lingual entity alignment remains an open challenge [4].

In recent years, Differential Evolution (DE) algorithms [5] have emerged as prominent methodologies for heterogeneous entity alignment. Lu et al. [6] introduced a novel approach to assessing semantic similarity between terms by integrating corpus-based and WordNet-based methods using the classic DE algorithm, yielding superior results compared to existing methods and aligning more closely with human judgment of similarity. Haque et al. [7] showd DE's effectiveness in adjusting voting weights in a heterogeneous entity classifier ensemble, enhancing the Matthews Correlation Coefficient and generalization across datasets. To address the problem of entity heterogeneity in the Internet of Everything (IoE) and Biomedical domains, Xue et al. [8, 9] employed a parallel DE with Adaptive Step Length (pcDE-ASL) algorithm to efficiently execute the entity mapping process, improving accuracy and efficiency in identifying identical entity pairs. Furthermore, Yue et al. [10] developed a multi-objective DE to simultaneously maximize the accuracy of heterogeneous entity recognition and minimize the number of selected features in speech emotion recognition, demonstrating superior performance across various English speech emotion datasets compared to other multi-objective algorithms. Despite these developments, the use of DE for solving the multi-lingual entity alignment issue is still limited because of the complex challenges arising from semantic differences between languages and the difficulties involved in aligning entities described in various linguistic contexts [11].

In this work, we propose a novel Hybrid DE (HDE) to efficiently determine multi-lingual entity mappings. Our contributions in this work are as follows:

- To effectively distinguish the heterogeneous multi-lingual entities, a novel multi-lingual similarity measure is proposed to measure the similarity between two multi-lingual entities. This metric works on the Babelnet Translate [1], and comprehensively integrate the syntax and linguistic information of different entities to enhance its discriminative power.
- To improve the efficiency of multi-lingual entity alignment process, a new HDE is developed. It uses a novel encoding mechanism to facilitate the search for optimal entity mapping set, and introduces a new local search strategy that uses multiple mutation strategies to help the algorithm escape the local optima.
- The OAEI's Multi-farm dataset [2] is used to test the performance of HGP, and the further analysis is made to validate each new components of HDE-based multi-lingual entity alignment method.

[1]https://babelnet.org/

[2]http://oaei.entitymatching.org/2018/multifarm/index.html

The remainder of the paper is structured as follows: Section 2 outlines classic DE and related work; Section 3 introduces the multi-lingual entity similarity measure; Section 4 delves into HDE for multi-lingual entity alignment; Section 5 presents experimental results and analysis; and finally, Section 6 concludes and discusses future work.

2. Background.

2.1. **Differential Evolution Algorithm.** Differential Evolution (DE) [12] stands out for its remarkable simplicity and effectiveness in tackling intricate optimization problems, making it a compelling choice for various applications. DE operates via mutation, crossover, and selection, using a population of real-valued vectors $X_{i,g} = (x_{i,1,g}, \ldots, x_{i,D,g})$, where i indexes the population from 1 to NP, and g indexes generations from 1 to $G_{textmax}$. The population size is NP and the problem dimensionality is D. Initialization involves setting each vector element as $x_{min,j} + rand(0,1) \cdot (x_{max,j} - x_{min,j})$ for $j = 1, \ldots, D$, where $x_{min,j}$ and $x_{max,j}$ are the bounds for each dimension and $rand(0,1)$ is a uniform random number.

Mutation generates a donor vector $V_{i,g}$ for each target vector using various strategies.

$$V_{i,g} = X_{r1,g} + F \cdot (X_{r2,g} - X_{r3,g}) \tag{1}$$

$$V_{i,g} = X_{r1,g} + F \cdot (X_{r2,g} - X_{r3,g}) + F \cdot (X_{r4,g} - X_{r5,g}) \tag{2}$$

$$V_{i,g} = X_{best,g} + F \cdot (X_{r1,g} - X_{r2,g}) + F \cdot (X_{r3,g} - X_{r4,g}) \tag{3}$$

$$V_{i,g} = X_{i,g} + F \cdot (X_{r1,g} - X_{i,g}) + F \cdot (X_{r2,g} - X_{r3,g}) \tag{4}$$

where F is a positive scaling factor affecting the differential variation amplitude.

Crossover boosts diversity by merging mutation vector $V_{i,g}$ and target vector $X_{i,g}$ into trial vector $U_{i,g}$:

$$u_{i,j,g} = \begin{cases} v_{i,j,g} & \text{if } (\text{rand}_{i,j}(0,1) \leq CR \text{ or } j = j_{\text{rand}}) \\ x_{i,j,g} & \text{otherwise} \end{cases} \tag{5}$$

where CR is the crossover rate, a user-defined threshold.

Selection uses one-to-one competition, choosing between the trial and target vectors for the next generation based on their fitness. For minimization, the selection is:

$$X_{i,g+1} = \begin{cases} U_{i,g} & \text{if } f(U_{i,g}) \leq f(X_{i,g}) \\ X_{i,g} & \text{otherwise} \end{cases} \tag{6}$$

where $f(\cdot)$ represents the fitness of vectors $U_{i,g}$ and $X_{i,g}$.

2.2. **Related Work.** Recent multi-lingual entity matching approaches tend to use machine translation to convert the task into English-only matching. Khiat et al. [13] segment, normalize, and translate labels into English using Yandex. Similarly, Jimenez et al. [14] uses natural language processing techniques in each language and translates entities into English using Yandex, computing similarity values through Wordnet. Grace et al. [15] build a bilingual corpus from the Wall Street Journal and People's Daily, using TF-IDF and cosine metrics to compute similarity. Helou et al. [16] utilize Google Translate for interpretation, while Trojahn et al. [17] propose a translation-based multi-lingual entity alignment technique employing a multi-agent architecture.

Furthermore, Nagy et al. [18] utilize DBpedia to associate English and Dutch concepts, proposing the DSSim tool to solve monolingual entity alignment. Similarly, Bouma [19] employs EuroWordnet for English-to-Dutch translations and aligns Dutch acronyms with

Wordnet and DBpedia. The translation quality crucially affects performance, with potential misinterpretations degrading alignment. To mitigate this, we use Babelnet translate, noted for its superior concept mapping performance [2], converting the multi-lingual challenge into a monolingual context.

3. **Multi-lingual Entity Similarity Measure.** Multi-lingual entity similarity measures, foundational to alignment techniques [3], are computed using profile-based methods. For two multi-lingual concepts, we construct profiles from the labels of each concept and its direct ascendants and descendants. The similarity between entities e_1 and e_2 is then calculated with their profiles p^1 and p^2.

$$\frac{\sum_{i=1}^{|p^1|} \max_{j=1\cdots|p^2|}(sim'(p_i^1, p_j^2)) + \sum_{j=1}^{|p^2|} \max_{i=1\cdots|p^1|}(sim'(p_j^2, p_i^1))}{2 \times \min(|p^1|, |p^2|)} \tag{7}$$

where $|p^1|$ and $|p^2|$ denote the cardinalities of the profile sets p^1 and p^2, respectively. Specifically, p_i^1 and p_j^2 represent the ith element of p^1 and the jth element of p^2, respectively, enabling precise indexing within the profiles. Moreover, the function $sim'()$ is responsible for computing the similarity value between the elements p_i^1 and p_j^2, facilitating the comparison and evaluation of similarity between multi-lingual concepts within the alignment process.

Before computing $sim'(p_i^1, p_j^2)$, we employ natural language processing techniques and utilize Babelnet Translate[3], a comprehensive machine translation tool covering 271 different languages, as demonstrated to be effective in multi-lingual entity alignment [2], to preprocess p_i^1 and p_j^2. The preprocessing process encompasses a series of sequential steps. Firstly, it involves removing numbers, punctuation, and stop-words from the text. For example, consider the phrase "The quick brown fox jumps over the lazy dog". After this step, the phrase becomes "quick brown fox jumps lazy dog". Next, the text undergoes tokenization, where it is divided into individual words. Continuing with our example, the tokenized version of the phrase would be ["quick", "brown", "fox", "jumps", "lazy", "dog"]. Following tokenization, the words are translated into English and converted to lower-case. For instance, if any of the words were in another language, they would be translated to English, and all letters would be changed to lower-case. Finally, the lemmatization and stemming processes are applied to the English words, ensuring that different forms of words are reduced to their root forms. This results in a standardized representation of the text, facilitating further analysis or processing.

Subsequently, the similarity measure $sim'(p_i^1, p_j^2)$ is computed using soft TF-IDF [20]. For example, let's consider two concepts: "apple" in English and "pomme" in French. The soft TF-IDF algorithm computes the similarity between these concepts based on their frequency and importance in their respective contexts. Additionally, in determining similarity, two words are considered identical if they either match literally or are synonymous according to the English Wordnet [21]. This ensures a comprehensive assessment of similarity between concepts across languages. Furthermore, leveraging concept alignment, this matching process extends to object properties. For instance, consider two object properties: "weigh" and "mass". By computing similarity values for their respective domains and ranges, and subsequently determining identical data object properties based on their label similarity values, we ensure a thorough alignment process that captures semantic similarities beyond just concept labels.

[3]https://babelnet.org/

4. **Hybrid Differential Evolution Algorithm For Multi-Lingual Entity Alignment.** The Differential Evolution algorithm emerges as the preferred choice for multi-lingual entity matching, leveraging its inherent strengths in efficiently navigating complex and high-dimensional search spaces. Its population-based approach ensures diversity, enabling simultaneous exploration of a wide range of potential solutions—an essential feature for addressing the diverse languages and semantic nuances inherent in such matching tasks. DE's parameterization flexibility allows for tailored adjustments, accommodating the specific requirements and characteristics unique to multi-lingual entity matching challenges. Furthermore, its simplicity and ease of implementation make it widely accessible and adaptable across various applications, including multi-lingual entity matching, where robust and scalable solutions are crucial. However, to further enhance the effectiveness of DE in addressing the complexities of multi-lingual entity matching, we introduce the Hybrid Differential Evolution framework. By integrating innovative local search strategy, HDE aims to augment DE's capabilities, offering even greater robustness, adaptability, and efficiency in tackling the challenges inherent in multi-lingual entity matching tasks.

4.1. **Algorithm Overview.** To enhance the efficiency of the multi-lingual entity alignment process, a novel HDE framework has been developed, as illustrated in Figure 1. This framework introduces an innovative local search mechanism that employs various mutation strategies to help the algorithm avoid local optima. The HDE process begins with initialization, followed by fitness evaluation of the entities using the f-measure [22]. If the termination conditions are not satisfied, the algorithm moves on to breeding and re-evaluating fitness. Depending on the need for local search, it either returns to fitness evaluation or proceeds to the local search phase. In the local search phase, several breeding attempts are made to find the best local solution. This solution is then compared with the current elite solution; if it is better, the elite solution is updated, and the local search continues. If the local solution is not better than the elite solution, the local search ends, and a new round of evolution by DE begins.

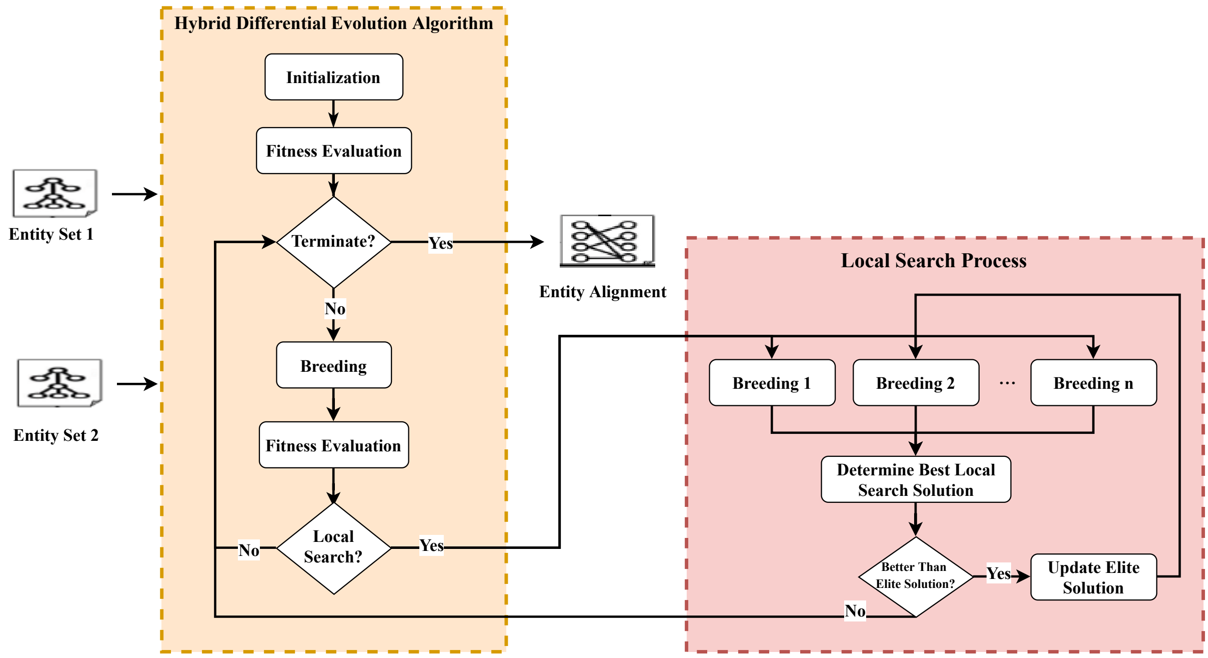


FIGURE 1. The framework of Hybrid Differential Evolution Algorithm.

In the next, we introduce the designed HDE in detail, concentrating on its two essential elements: the encoding mechanism and the local search strategy.

4.2. **Encoding Mechanism.** The encoding mechanism implemented in this study utilizes Gray Encoding [23], to map source entities to their corresponding target entities. Gray Encoding is distinguished by its property, where adjacent values differ by only a single bit. This characteristic significantly reduces the probability of transition errors. Each target concept is systematically assigned a unique index, which is then encoded into a Gray code sequence. This sequence constitutes the genetic information on a chromosome. During the decoding process, the Gray code is converted back into the numerical index, accurately identifying the associated target concept. To handle cases where a source concept does not map to any target concept, a specific Gray code, typically represented by all zeros, is employed.

For example, the source entity "pharynx epithelium", indexed as 4, is mapped to the target entity "Oropharynx Epithelium", also indexed as 4. The Gray code corresponding to this mapping on the chromosome is "010". Upon decoding, this Gray code reverts to the index 4, directly pinpointing "Oropharynx Epithelium" as the target. This example illustrates the efficacy of Gray Encoding in maintaining the integrity of mappings between complex biological entities. Such precise encoding and decoding mechanisms are crucial for ensuring accurate, error-resistant data representation, especially in fields that involve genetic algorithms where robustness against data transmission errors is paramount.

4.3. **Local Search Strategy.** The execution of the local search process serves a critical purpose in helping DE transcend local optima, especially in the context of multi-lingual entity matching where the vast search space often leads to entrapment. Local optima are suboptimal solutions that DE may converge to prematurely, failing to explore the full solution space effectively [24]. By activating the local search when the elite individual remains unchanged for *delta* generations, we introduce a mechanism to systematically explore the vicinity of promising solutions. This allows DE to break free from local optima by iteratively refining the elite individual through diverse mutations and breeding operators. Consequently, the local search process enables DE to navigate the complex and expansive search space inherent in multi-lingual entity matching, facilitating the discovery of more globally optimal solutions and enhancing the algorithm's overall performance.

The pseudocode for the local search process is illustrated in Algorithm 1. The process starts by applying various breeding operators to the elite individual $indiv_{elite}$, incorporating different mutations as specified in Equations 1 to 4, thereby creating multiple populations $\mathcal{P}_{local}$. Next, the optimal local search solution, referred to as $indiv_{local}$, is selected from $\mathcal{P}_{local}$. We then evaluate if $indiv_{local}$ offers an improvement over $indiv_{elite}$; if it does, $indiv_{elite}$ is updated and subjected to another round of local search. This iterative process continues until no further improvements are found, at which point the final $indiv_{elite}$ is produced. By systematically exploring potential enhancements to the elite individual, the local search algorithm enables DE to overcome local optima, allowing it to more effectively traverse the complex and extensive solution space inherent in multi-lingual entity matching.

5. Experimental Studies.

5.1. **Experimental Setup.** To evaluate the performance of the developed HDE, we employ the Multi-farm dataset from OAEI, available at [4]. This dataset includes 45 unique language pairings, such as ar-cn, ar-cz, and ar-de, where each pair signifies a different

[4]https://oaei.ontologymatching.org/2022/multifarm/index.html

Algorithm 1: Local Search

Input: Population $\mathcal{P}$, Elite Individual $indiv_{elite}$, Breeding Operator Set $\mathcal{B}$
Output: $indiv_{elite}$

while *true* **do**
  $\mathcal{P}_{local} = \emptyset$; **for** *each breeding operator* $b_i \in \mathcal{B}$ **do**
    $\mathcal{P}_{local} = \text{breeding}(\mathcal{P}, indiv_{elite}, b_i)$;
  end
  $indiv_{local} = \text{optimal}(\mathcal{P}_{local})$;
  if $indiv_{local}$ *is better than* $indiv_{elite}$ **then**
    $indiv_{elite} = indiv_{local}$;
    continue;
  end
  else
    break;
  end
end
return $indiv_{elite}$.

combination of languages like Arabic and Chinese (ar-cn) or Chinese and French (cn-fr). These pairs offer extensive opportunities for testing entity alignment methods across varied language scenarios. Additional details can be found on the Multifarm track at the OAEI official website. We conduct a statistical analysis to compare the alignment quality between GA [25], MA[26], and participants from OAEI involved in the Multifarm track, namely CIDER-LM [27], LSMatch and LSMatch multi-lingual [28], LogMap, and LogMapLt [29]. We utilize the f-measure as the metric for assessing the quality of the alignments. The outcomes from OAEI participants are sourced from OAEI's official website [5]. The setups for GA and MA are detailed in their respective publications. The results for HDE displayed in the tables represent the average of thirty independent runs, with a configuration designed empirically to maximize average alignment quality across all test scenarios: population size: 60; maximum generation: 1000; scaling parameter F: 0.2; crossover rate CR: 0.6; generation threshold θ for initiating local search: 40, and a local search population size: 10.

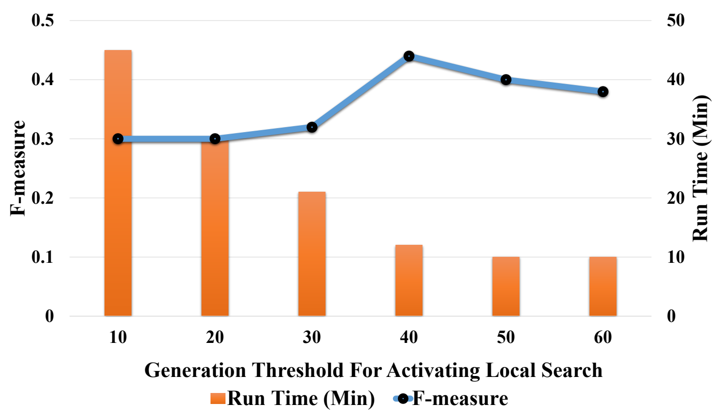


Figure 2. Sensitivity testing on the generation threshold θ for activating local search.

[5]https://oaei.ontologymatching.org/2022/results/multifarm/index.html

5.2. **Sensitivity Analysis on Parameter.** Figure 2 presents the results of sensitivity testing for different generation thresholds θ for activating local search, showcasing their impact on f-measure and run time. On the x-axis, the thresholds range from 10 to 60, while the y-axes measure f-measure and run time (minutes). The f-measure peaks at a threshold of 40, where it slightly exceeds 0.4, indicating the highest efficiency in terms of search result quality at this setting. Simultaneously, the run time at this threshold is maintained at around 40 minutes, reflecting a balance between computational efficiency and effectiveness of the local search. At thresholds higher than 40, both the f-measure and run time start to decline, suggesting that increasing the threshold beyond 40 leads to diminished returns in terms of both performance and efficiency. Therefore, a generation threshold of 40 is optimal for activating local search, as it maximizes f-measure while keeping run time reasonable.

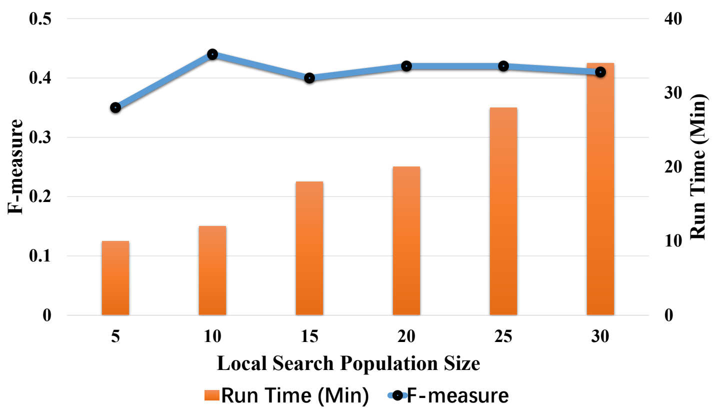


FIGURE 3. Sensitivity testing on local search population size.

Figure 3 depicts the impact of varying local search population sizes on both the f-measure and the computational run time in minutes. The x-axis represents the local search population sizes, ranging from 5 to 30, while the y-axis on the left measures the f-measure, and the right y-axis shows the run time. As observed, the f-measure peaks at a population size of 10 with a value just under 0.4, while the corresponding run time remains relatively low, around 10 minutes. This suggests that a local search population size of 10 strikes an optimal balance, achieving a high f-measure with a manageable run time. Beyond this point, increasing the population size significantly increases the run time without substantial improvement in f-measure, notably at sizes 25 and 30, where the run time escalates sharply to nearly 35 minutes. This analysis indicates that a population size of 10 is the most effective setting for this sensitivity testing.

5.3. **Experimental Results and Analysis.** In this work, statistical comparisons among various approaches are conducted using a multiple comparison procedure. Initially, the Friedman's test [30] assesses if there are any differences in results; if differences are identified, the Holm's test [31] is then applied to evaluate if one approach statistically surpasses the others.

Friedman's test assesses significant differences among algorithms, assuming equivalence under the null hypothesis; rejecting it indicates performance variations [32]. To reject, $\mathcal{X}_r^2$ must exceed the critical chi-square value [33]. We set $\alpha = 0.05$ for 8 approaches, the critical value $\mathcal{X}_{0.05}^2$ for 7 degrees of freedom is 14.07. Table 1 shows $\mathcal{X}_r^2$ at 278.4, surpassing the critical value and leading to the null hypothesis rejection, confirming significant differences. This requires a post-hoc analysis using Holm's procedure, with HDE as the control algorithm due to its lowest ranking in Table 1. Holm's test compares the control algorithm with others using the z value as the test statistic to compute p-values from the normal distribution. Assessed at a significance level of $\alpha = 0.05$, the results in Table 2 show that HDE significantly outperforms other methods in f-measure at this level.

Table 1. Friedman's test on the alignment's quality.

Test Case	CIDER-LM	LSMatch	LSMatch Multi-lingual	LogMap	LogMapLt	GA	MA	HDE
ar-cn	0.23 (3.5)	0.12 (8.0)	0.18 (6.0)	0.15 (7.0)	0.19 (5.0)	0.29 (2.0)	0.23 (3.5)	0.34 (1.0)
ar-cz	0.35 (2.5)	0.19 (8.0)	0.35 (2.5)	0.22 (7.0)	0.29 (5.0)	0.32 (4.0)	0.27 (6.0)	0.38 (1.0)
ar-de	0.32 (2.5)	0.21 (8.0)	0.32 (2.5)	0.23 (7.0)	0.26 (6.0)	0.31 (4.5)	0.31 (4.5)	0.41 (1.0)
ar-en	0.35 (3.0)	0.22 (8.0)	0.36 (2.0)	0.26 (7.0)	0.29 (6.0)	0.33 (4.0)	0.30 (5.0)	0.39 (1.0)
ar-es	0.39 (2.0)	0.18 (8.0)	0.31 (5.0)	0.21 (7.0)	0.29 (6.0)	0.36 (3.0)	0.33 (4.0)	0.43 (1.0)
ar-fr	0.33 (2.0)	0.17 (8.0)	0.25 (5.0)	0.19 (7.0)	0.23 (6.0)	0.31 (4.0)	0.32 (3.0)	0.37 (1.0)
ar-nl	0.34 (3.0)	0.19 (8.0)	0.36 (2.0)	0.21 (7.0)	0.24 (6.0)	0.30 (4.5)	0.30 (4.5)	0.40 (1.0)
ar-pt	0.43 (1.5)	0.24 (7.0)	0.33 (3.5)	0.23 (8.0)	0.27 (6.0)	0.33 (3.5)	0.31 (5.0)	0.43 (1.5)
ar-ru	0.25 (5.0)	0.19 (7.0)	0.36 (2.0)	0.18 (8.0)	0.24 (6.0)	0.28 (4.0)	0.30 (3.0)	0.40 (1.0)
cn-cz	0.28 (3.0)	0.15 (8.0)	0.23 (5.0)	0.17 (7.0)	0.20 (6.0)	0.27 (4.0)	0.29 (2.0)	0.31 (1.0)
cn-de	0.31 (3.0)	0.20 (7.5)	0.20 (7.5)	0.21 (6.0)	0.30 (4.5)	0.32 (2.0)	0.30 (4.5)	0.35 (1.0)
cn-en	0.28 (2.0)	0.23 (5.0)	0.19 (8.0)	0.20 (7.0)	0.21 (6.0)	0.26 (3.0)	0.24 (4.0)	0.31 (1.0)
cn-es	0.36 (2.0)	0.16 (8.0)	0.21 (6.0)	0.20 (7.0)	0.26 (5.0)	0.32 (3.0)	0.30 (4.0)	0.41 (1.0)
cn-fr	0.35 (2.0)	0.17 (8.0)	0.19 (6.0)	0.18 (7.0)	0.24 (5.0)	0.30 (3.0)	0.27 (4.0)	0.42 (1.0)
cn-nl	0.30 (4.0)	0.16 (8.0)	0.18 (7.0)	0.21 (6.0)	0.24 (5.0)	0.36 (2.0)	0.33 (3.0)	0.41 (1.0)
cn-pt	0.36 (2.0)	0.18 (8.0)	0.21 (6.0)	0.20 (7.0)	0.22 (5.0)	0.31 (3.0)	0.26 (4.0)	0.41 (1.0)
cn-ru	0.34 (2.0)	0.18 (8.0)	0.27 (3.0)	0.19 (7.0)	0.24 (4.0)	0.23 (5.0)	0.21 (6.0)	0.39 (1.0)
cz-de	0.41 (2.0)	0.30 (6.0)	0.34 (5.0)	0.24 (8.0)	0.26 (7.0)	0.37 (3.5)	0.37 (3.5)	0.46 (1.0)
cz-en	0.42 (3.0)	0.27 (7.0)	0.44 (2.0)	0.23 (8.0)	0.28 (6.0)	0.38 (5.0)	0.40 (4.0)	0.49 (1.0)
cz-es	0.50 (2.0)	0.27 (8.0)	0.34 (5.0)	0.29 (7.0)	0.31 (6.0)	0.36 (4.0)	0.42 (3.0)	0.55 (1.0)
cz-fr	0.47 (2.0)	0.23 (7.0)	0.34 (5.0)	0.21 (8.0)	0.27 (6.0)	0.39 (3.0)	0.35 (4.0)	0.50 (1.0)
cz-nl	0.49 (2.0)	0.26 (8.0)	0.39 (3.5)	0.27 (7.0)	0.30 (6.0)	0.39 (3.5)	0.37 (5.0)	0.52 (1.0)
cz-pt	0.48 (2.0)	0.36 (7.0)	0.38 (5.0)	0.34 (8.0)	0.37 (6.0)	0.45 (3.0)	0.41 (4.0)	0.52 (1.0)
cz-ru	0.45 (2.0)	0.31 (6.5)	0.40 (3.5)	0.24 (8.0)	0.31 (6.5)	0.38 (5.0)	0.40 (3.5)	0.50 (1.0)
de-en	0.41 (2.0)	0.34 (6.0)	0.38 (3.0)	0.29 (8.0)	0.31 (7.0)	0.36 (4.5)	0.36 (4.5)	0.44 (1.0)
de-es	0.42 (2.0)	0.29 (8.0)	0.34 (5.5)	0.31 (7.0)	0.34 (5.5)	0.40 (3.0)	0.38 (4.0)	0.44 (1.0)
de-fr	0.44 (2.0)	0.25 (8.0)	0.37 (5.0)	0.33 (7.0)	0.35 (6.0)	0.40 (3.5)	0.40 (3.5)	0.46 (1.0)
de-nl	0.42 (2.0)	0.30 (6.0)	0.39 (3.0)	0.27 (8.0)	0.29 (7.0)	0.37 (4.0)	0.33 (5.0)	0.45 (1.0)
de-pt	0.43 (2.0)	0.36 (6.0)	0.33 (8.0)	0.34 (7.0)	0.37 (5.0)	0.39 (3.5)	0.39 (3.5)	0.46 (1.0)
de-ru	0.35 (4.0)	0.24 (8.0)	0.38 (2.0)	0.27 (7.0)	0.30 (6.0)	0.36 (3.0)	0.34 (5.0)	0.42 (1.0)
en-es	0.39 (2.5)	0.26 (8.0)	0.39 (2.5)	0.30 (7.0)	0.35 (5.0)	0.38 (4.0)	0.34 (6.0)	0.40 (1.0)
en-fr	0.39 (2.0)	0.23 (8.0)	0.37 (3.0)	0.26 (7.0)	0.29 (6.0)	0.36 (4.5)	0.36 (4.5)	0.43 (1.0)
en-nl	0.42 (3.0)	0.28 (6.0)	0.47 (1.5)	0.22 (8.0)	0.26 (7.0)	0.36 (4.0)	0.34 (5.0)	0.47 (1.5)
en-pt	0.43 (3.0)	0.34 (6.0)	0.46 (2.0)	0.28 (8.0)	0.31 (7.0)	0.39 (5.0)	0.42 (4.0)	0.50 (1.0)
en-ru	0.33 (5.0)	0.26 (6.5)	0.42 (2.0)	0.24 (8.0)	0.26 (6.5)	0.39 (3.0)	0.34 (4.0)	0.44 (1.0)
es-fr	0.47 (2.0)	0.25 (8.0)	0.35 (5.0)	0.29 (7.0)	0.32 (6.0)	0.45 (3.0)	0.40 (4.0)	0.49 (1.0)
es-nl	0.50 (1.5)	0.29 (7.5)	0.35 (5.0)	0.29 (7.5)	0.30 (6.0)	0.42 (3.0)	0.39 (4.0)	0.50 (1.5)
es-pt	0.50 (1.5)	0.34 (6.0)	0.39 (5.0)	0.28 (8.0)	0.30 (7.0)	0.45 (3.0)	0.43 (4.0)	0.50 (1.5)
es-ru	0.44 (2.0)	0.34 (6.5)	0.35 (5.0)	0.31 (8.0)	0.34 (6.5)	0.43 (3.0)	0.41 (4.0)	0.48 (1.0)
fr-nl	0.47 (2.0)	0.23 (8.0)	0.36 (5.0)	0.26 (7.0)	0.30 (6.0)	0.40 (3.0)	0.38 (4.0)	0.49 (1.0)
fr-pt	0.47 (2.0)	0.29 (8.0)	0.33 (6.0)	0.30 (7.0)	0.36 (5.0)	0.42 (3.0)	0.39 (4.0)	0.48 (1.0)
fr-ru	0.42 (2.0)	0.26 (8.0)	0.31 (6.0)	0.28 (7.0)	0.32 (5.0)	0.39 (3.5)	0.39 (3.5)	0.45 (1.0)
nl-pt	0.51 (2.0)	0.31 (8.0)	0.39 (5.0)	0.32 (7.0)	0.36 (6.0)	0.45 (3.5)	0.45 (3.5)	0.53 (1.0)
nl-ru	0.44 (2.0)	0.25 (8.0)	0.40 (4.0)	0.28 (7.0)	0.30 (6.0)	0.42 (3.0)	0.38 (5.0)	0.47 (1.0)
pt-ru	0.42 (2.0)	0.32 (7.0)	0.41 (3.5)	0.29 (8.0)	0.33 (6.0)	0.41 (3.5)	0.36 (5.0)	0.47 (1.0)
Avg.	0.40 (2.2)	0.25 (7.6)	0.35 (4.2)	0.25 (7.3)	0.32 (5.8)	0.36 (3.5)	0.35 (4.3)	0.44 (1.1)

Table 2. Holm's test on the alignment's quality.

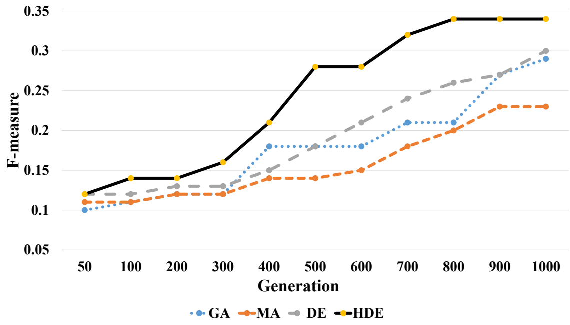
i	approach	z value	unadjusted $p-$value	$\frac{\alpha}{k-i}, \alpha = 0.05$
7	CIDER-LML	2.2	0.023	0.050
8	GA	3.5	1.15×10^{-3}	0.025
5	LSMatch Multi-lingual	4.2	5.42×10^{-5}	0.016
4	MA	4.3	1.16×10^{-8}	0.012
3	LogMapLt	5.8	4.54×10^{-12}	0.010
2	LogMap	7.3	3.02×10^{-16}	0.008
1	LSMatch	7.6	9.26×10^{-19}	0.007

The local search strategy is critical to improve the performance of designed HDE, to test its effectiveness, Figure 4 compares it with GA, MA and DE (non-local search version of HDE) in terms of convergence graph on six representative test cases. In the ar-cn test case, GA and MA show steady but modest improvements, peaking at F-measures of 0.15 and 0.2 respectively, while DE achieves 0.25. HDE surpasses all, starting on par with DE and climbing sharply to stabilize at 0.35, showing its superior integration of exploration and exploitation techniques. In the cn-cz scenario, HDE again demonstrates its efficiency, starting alongside DE and achieving a consistent ascent to the same F-measure of 0.35, significantly outperforming the modest gains shown by GA and the slight improvements of MA. The cz-de case mirrors this, with HDE starting at similar levels but rising to a high of 0.45, emphasizing its robust hybrid strategies. In the de-en test, HDE's trajectory markedly improves early and maintains growth to about 0.4, demonstrating superior optimization capabilities over the other algorithms. Similarly, in en-es, HDE rapidly separates from the pack to reach an F-measure near 0.45, effectively utilizing various strategies for optimal results. Finally, in the es-fr test, HDE again shows significant performance enhancements, stabilizing near 0.45 and confirming its dominance across multiple scenarios through advanced hybrid strategies that maximize the strengths of differential evolution with additional techniques.

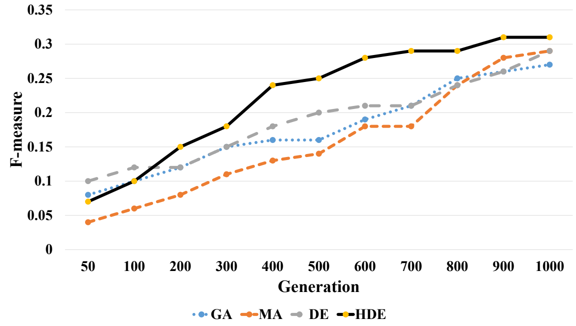
The experimental findings strongly validate the efficacy of the developed HDE, which integrates sophisticated local search strategies with various mutation techniques, to improve the efficiency of the multi-lingual entity alignment process. In six representative test cases, HDE consistently surpassed traditional algorithms like GA, MA, and the non-local search version DE, achieving higher F-measure values and showcasing superior optimization capabilities. This performance highlights HDE's effective combination of exploration and exploitation techniques, especially its ability to avoid local optima and explore new potential solutions in multi-lingual entity alignment. The consistent performance of HDE across different scenarios emphasizes the robustness and adaptability of its local search component, making it a versatile and effective solution for optimizing the entity alignment process across multiple languages.

6. **Conclusion and Future Work.** This paper proposes a novel HDE approach aimed at automating the identification of high-quality multi-lingual entity alignments. Distinguished from conventional EA-based methods, HDE incorporates a new multi-lingual similarity measure, an innovative encoding mechanism, and a novel local search strategy to enhance the algorithm's search performance. Empirical evaluations validate the effectiveness of the designed HDE in generating high-quality multi-lingual entity mappings, showing superior performance compared to state-of-the-art multi-lingual entity matching methods. In particular, the introduced local search strategy significantly enhances the efficiency of HDE, facilitating its ability to navigate away from local optima.

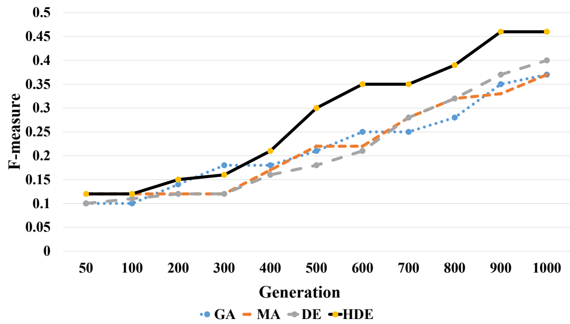
In the future, enhancing the effectiveness and applicability of the HDE approach for multi-lingual entity alignment can be achieved through several avenues. Firstly, integrating additional linguistic resources or ontologies could enrich the multi-lingual similarity measure, with preliminary efforts focusing on assessing compatibility and addressing integration challenges. Secondly, exploring advanced encoding mechanisms or representation learning techniques could capture nuanced semantic relationships between entities, with specific techniques identified through preliminary experiments. Moreover, incorporating domain-specific knowledge or context-aware features could enhance adaptability, with initial investigations conducted in specific domains to identify relevant features and assess their impact. Additionally, conducting extensive experiments on larger and more diverse datasets would provide insights into scalability and robustness, with preliminary



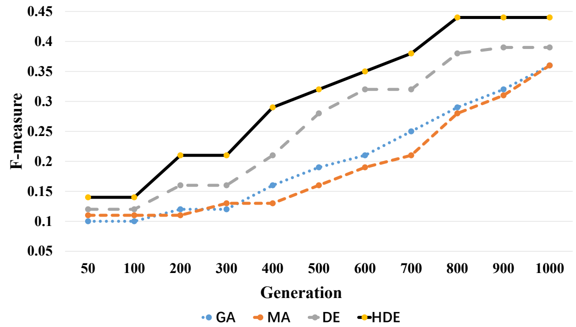
(a) ar-cn



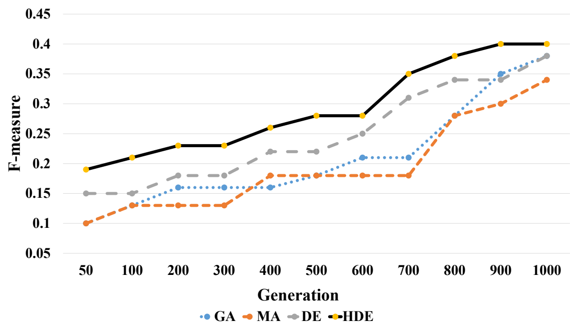
(b) cn-cz



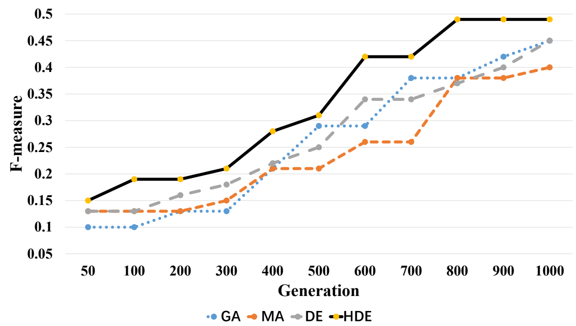
(c) cz-de



(d) de-en



(e) en-es



(f) es-fr

FIGURE 4. Comparisons among GA, MA, DE and HDE on the converge graph over 30 independent runs in representative test cases.

experiments on smaller datasets or synthetic data highlighting potential challenges. Furthermore, exploring parallelization or distributed computing strategies could expedite computation-intensive tasks, with initial investigations focusing on feasibility and effectiveness. Finally, integrating machine learning techniques like deep learning [34] or other optimization algorithm [35] could optimize the search process, with preliminary experiments or comparative studies shedding light on potential benefits. Addressing these avenues and discussing preliminary efforts or challenges faced in each area will advance the state-of-the-art in multi-lingual entity alignment, fostering broader adoption across domains and applications.

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