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AIDEN: A Density Conscious Artificial Immune System for Automatic Discovery of Arbitrary Shape Clusters in Spatial Patterns

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Abstract

Recent efforts in modeling of dynamics of the natural immune cells leading to artificial immune systems (AIS) have ignited contemporary research interest in finding out its analogies to real world problems. The AIS models have been vastly exploited to develop dependable robust solutions to clustering. Most of the traditional clustering methods bear limitations in their capability to detect clusters of arbitrary shapes in a fully unsupervised manner. In this paper the recognition and communication dynamics of T Cell Receptors, the recognizing elements in innate immune system, has been modeled with a kernel density estimation method. The model has been shown to successfully discover non spherical clusters in spatial patterns. Modeling the cohesion of the antibodies and pathogens with '*local influence*' measure inducts comprehensive extension of the antibody representation ball (ARB), which in turn corresponds to controlled expansion of clusters and prevents *overfitting*.

Keywords: Artificial Immune System; Density Based Clustering; spatial patterns

1. Introduction

The mechanism of artificial immune systems (AIS) has been comprehensively applied in unsupervised learning problems, for example the tasks of anomaly detection and of clustering. Imitation of the recognition process of natural immune cells eventually imposes grouping of 'self' and 'non-self' patterns. The recognition process of the natural immune cells has been modeled using a variety of formulations comprising of mathematical and statistical principles leading to several models of AIS [1][2][3]. Given the heavily complex internal communication structure of immune system, models exploiting holistic analogies of the same have been rare in literature. Selective interpretations of the internal functionality and interaction among the immune system components have generated dependable solutions to a wide range of applications with typical characteristic constraints.

The task of clustering data in $\Re^N$ carries several challenges including arbitrary shapes of inherent clusters, automatic detection of clusters, and robustness against noise besides others. Further, the algorithm must also address the issues of scalability and robustness. Preliminary schemes like the hierarchical and the partitioning based clustering methods have been largely utilized in serving several clustering applications. However these clustering processes essentially depend on user intervention either before start of the learning (prior specification of cluster number K in K-means) or after the completion of clustering process (for interpretation of relevant clustering level in hierarchical clustering). One standard approach addressing such issues includes the generative models, wherein algorithms like EM are used to learn mixture densities. These models have proven capability of automatic detection of clusters inherent in the input data. The initial generative models suffer from limitations like the need for simplifying assumptions of Gaussian density of clusters, occurrence of local minima of the log likelihood, and their sensitiveness to initialization of model parameters, for example the mean and the std. deviation in case of the Gaussian mixtures [4]. Several stochastic models have been reported to deal with the limitations of the generative models. Few remarkable models applied Markov Chain Monte Carlo (MCMC) method to improve robustness amidst missing values [5]. Solutions employing non Gaussian mixtures from the exponential families have also been shown to be capable of detecting arbitrary shapes of cluster [5] [6]. Majority of such promising schemes with strong theoretical foundations have been found to be expensive in implementation. Recent computing applications have incorporated extensive involvement of a variety of data types e.g. spatial data with inherent complex characteristics namely existence of non linear and overlapping segments/classes. Development of improved data clustering models to aptly handle such underlying issues is a research topic of great interest. Recently spectral clustering method has emerged as a favorable alternative applied in several applications in machine learning [2]. In this method, the top eigenvectors of a matrix derived from the distance matrix of data points are used to derive clusters. Spectral analysis has also been widely used in analysis of patterns in spatial data [3] [4]. However, implementation of this method poses difficulty in decision about which eigenvector to use and to derive clusters from them [2].

This paper presents a clustering method based on artificial immune system (AIS). AIS essentially imitates the recognition process of the natural immune cells to detect pathogen, learn the patterns, and develop antibodies to attack any future occurrence of such pathogens. The mechanism of AIS has found its application in the task of clustering, since the imitation of the recognition process of the immune cells eventually imposes grouping of 'self' and 'non-self' patterns. The present work reports modeling and results of implementation of Artificial Immune system with DENsity sensitiveness (AIDEN). AIDEN in principle exploits the inherent density-closeness of the items in the input dataset to automatically discover the inherent cluster. The experiments show the utility of the model in clustering of spatial patterns. The robustness, scalability, and convergence of the algorithm have been discussed in relevant section.

2. Functional Elements of Artificial Immune System

The immune system involves complex interaction between four major components in fighting off pathogens: i) Antibodies ("immunoglobulins") and the (B) cells that make them, ii) Complement iii) T cells, and iv) Non-specific effector cells [7]. B Cells essentially make the Antibodies which specifically bind to pathogens and pass them to the Complement and phagocytic cells. A Complement is a cascade of small proteins that bind to pathogens and poke holes in their outer surface causing death. Complement proteins can bind to some pathogens directly but the activity of Complement is much amplified by the presence of antibody bound to the pathogen. The T Cells help the B cells become antibody producing cells (APC) and help other cells perform effector functions. Various ways to model an approximate function of the immune systems have been proposed in literature [9]. Non-specific effector cells like macrophages and neutrophils kill pathogens, much effectively if antibody is bound to the pathogen. Other effector cells, like NK cells kill self cells that have been infected with pathogens (such as viruses). The Mast cells secrete factors that create inflammation in the area of the pathogen to allow rapid access of other immune components to the site. The T lymphocyte (T cell) in a mammalian immune system is capable of performing fine grain discrimination of peptide bound Major Histocompatibility Complex (pMHC) molecules on APCs through its T cell Receptor (TCR) and intracellular signaling network. So it discriminates between abundant self-pMHC all pMHC on an APC, and non-self-pMHC [8][10][11].

Biologically, TCRs induce activation signal in a T-cell through a process involving the steps of kinetic proofreading, negative feedback, negative feedback destruction, and tuning. Kinetic proofreading involves energy consumption steps that must be overcome before TCR may generate an activation signal. The negative feedback generated through progression of the kinetic proofreading eventually reverses the process regardless of the TCR-pMHC binding strength.

However on successful completion of kinetic proofreading a TCR generates activation signal which is then amplified and provides protection to all other TCRs from the negative feedback. The coreceptor density can be understood as a tuning parameter, small increases in which increases the probability of activation.

3. Dynamic Density Conscious Clustering with T-Cell Receptor Signaling

A natural correspondence between the biological T Cell receptor signaling and kernel density estimation was established in [10]. We observe selective analogies of the biological features of the signaling and immunization dynamics of TCell-BCell-APC configuration of the immune system in the context of density-conscious clustering. The kinetic proofreading by a single TCell through its receptor and the co-receptor (CD8) tuning can be modeled using the concept of *k*-nearest-neighbors based '*density-reachability*' applied in density based clustering technique DBSCAN [9]. The present work shows that the static stimulation of the TCRs and the dynamic behavior of the immune system resulting from intra-cellular interactions can be modeled in the perspective of density conscious cohesions. The cohesion measurement has been modeled using the concept of *k*-nearest neighborhood and local-density-factor.

We consider a stream of points x1, x2, x3 . . . ∈ x at receptors positions t1, t2, t3 . . . ∈ $\Re^N$.

The stimulation of TCR on presentation of a pathogen, as a result of kinetic proofreading can be represented with a receptor stimulation r_p (x) and negative feedback r_n(x) at all points in $\Re^N$, as given in equation (1) and equation (2). The static receptor stimulation may be generated by a function *f* (.), which is a model parameter, exemplified in the section describing the algorithm.

$$r_p(x) = f(r_p, x) \qquad \text{-- (1)}$$

$$r_n(x) = \begin{cases} r_p(x) - \beta \text{ if } r_p(x) > \beta \\ 0 \quad \text{otherwise} \end{cases} \qquad \text{--(2)}$$

A TCR at position p is stimulated if r_p (x) - r_n(x) > *l*. Figure 1 depicts this process. When a T Cell receives stimulations on more than k receptors, it generates activation signal to a B Cell, as represented in Figure2.

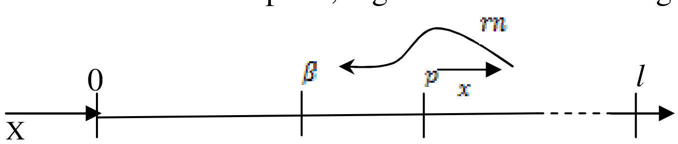

Figure1. Static stimulation of a single TCR- The kinetic proofreading by the receptor on input x Є X forwards the receptor position p toward l. The receptor will generate negative feedback if p > β. The receptor will generate success signal when p== l.

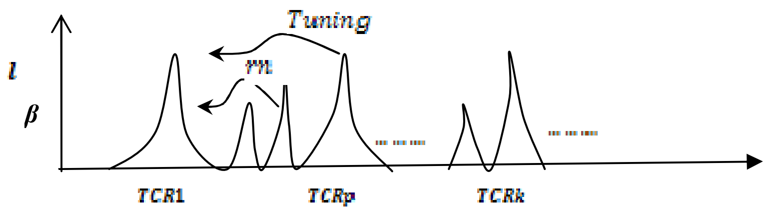

Figure2. Generation of negative feedbacks gets tuned once a TCR completes stimulation beyond the threshold l. A TCell generates activation signal to BCell once it gets stimulation of its k-TCRs.

On receiving activation signal from TCell, a BCell produces *k*-antibodies in the APC associated with it, corresponding to the pathogens stimulating respective T Cell. Intercellular interaction among BCells give rise to antigen recognition balls (ARBs). APCs connect together if their *inter-cell-cohesion factor (cf)* is beyond a threshold ψ. To formulate *cf* for our model, the concept of local scaling [12][13], which was originally introduced to determine the scale factor for clusters with different densities by scaling the distances around each point in the dataset with a factor proportional to its distance to its *k*th nearest neighbor. Typically ψ is taken as $2^{-\alpha}$, α being another model parameter determined by the data characteristics. Figure3 depicts this process. The model with the above specification then effectively detects self or non-self pathogens. In terms of its application to the task of clustering, this interpretation means making the affinities high within clusters and low across clusters. A pathogen corresponding to an outlier would not stimulate a TCR sufficiently and may not form part of any ARB.

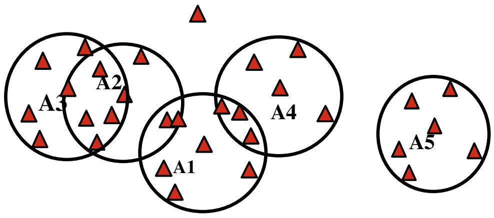

Figure3. APCs A1-A4 connected within range of cohesion-factor-threshold form members of one ARB, while A5 lies there single and is likely to form another ARB with progress of the recognition process. The single point represents a pathogen not sufficiently stimulating any TCR and corresponds to an outlier.

4. Algorithm and Explanation

AIDEN()
Input: D: Ag-Ab Affinity matrix, k: input to *kNN*-dist function, n: number of dimensions, cohesion_factor_threshold (ψ)
Output: Allocation of points to clusters.
begin
    for pgen Є *Pathogens* **do**
        pgen.*ARB* = *UNDETERMINED*;
        [pgen. *BestAffinedist*, pgen.affines] = *kNNDistVal*(D, pgen, k);
    end
    Pathogens.sort(); /* Sort on *BestAffinedist* */
    arbID = 1;
    for pgen Є *Pathogens* **do**
        if pgen.*ARB* == *UNDETERMINED* **and** *localDense*(pgen) **then**
            ARBGrow (pgen, *arbID*, n, ψ);
            arbID = *arbID* + 1;
        end
    end
end

ARBGrow()
Input: pgen, *arbID*, n, ψ
Output: ARB corresponding to current Id Extended with inclusion of APCs with sufficient local-cohesion.
begin
    pgen.ARB = *arbID*;
    APC= pgen.affines
    for Ag Є APC
        if Ag.ARB == *UNDETERMINED*
            Ag.ARB = *arbID*;

```
            else
                  APC.remove(Ag)
            end if
      end for
      while Exists (APC)
            Ag = APC.next()
            if   Ag.BestAffinedist ≤ ψ x pgen. BestAffinedist
                  newAgs = Ag.affines
                  for nAg Є newAgs
                        if nAg.ARB == UNDETERMINED
                        APC.append(nAg)
                              nAg.ARB = arbID
                        end if

                  end for
            end if
            APC.remove(nAg)
      end while
end
```

5. Explanation of the Implementation and Experimental Results

The algorithm presented above implements the model described in section 3. The input matrix D provides the values for $f(x_i, x_j)$ in Equation 1. All checks related to stimulations at various stages would use this matrix only for the purpose. To keep the translation simple, it has been assumed that the value of β is set much higher, as a system parameter itself, so that its effect is nullified by equation 2. For the same reason, the effects of negative feedback destruction and that of tuning are rendered theoretically running in the background, hence having no direct mention in the above implementation. The function *localDense*(pgen) determines from among the unclassified data-point in *k*-nearest-neighborhood of *pgen* having highest density estimated on the basis of proximity of their own k-NN elements . Further, ARBGrow() implements the ARB formation and expansion process discussed in the section 3.

The program was implemented in Matlab and tested with several patterns. The first, dataset1 consisted of 2 patterns each comprised of 100 points falling on two concentric circles of radii 10 and 20 respectively. The second, dataset2 consisted of 3 patterns each of 100 points falling on three concentric circles of radii 10, 15, and 20 respectively. The model was further tested for its capability to find clusters in patterns of open spatial form using dataset3 and dataset4 consisting of 200 and 300 points falling on 2 and 3 concentric semi circles respectively. As shown in the Figure2.a and Figure2.b, the algorithm is capable of determining spatial association of a data point with other data points belonging to its appropriate circle only. The results successfully demonstrated the capability of our model to automatically detect clean clusters of arbitrary shapes in the input data represented in closed spatial form. The model was found even capable of determining clusters of open spatial forms also, as shown in Figure2.c and Figure2.e. However, the output of the algorithm was found affected by the values of the algorithm parameters k and α. In the present experiment, k =8 and α =10 was sufficient for performing correct cluster associations. On the other hand, correct clustering for the dataset2, could be obtained with 10NN estimation i.e. k =10, with α=15. Moreover setting k =15, with α=15 was required for dataset4, as clustering error was observed with k =10, with α=15, as in Figure2.d. Figure2.f and Figure2.g show the correct clustering even in presence of combination of open and closed form of input patterns. In each figure, the first sub-plot shows the original data and the second sub-plot shows the clusters identified by our program.

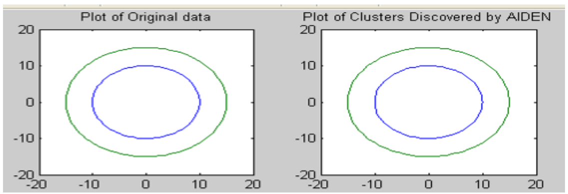

Figure2.a. dataset1. k=8(10), alpha=10(15)

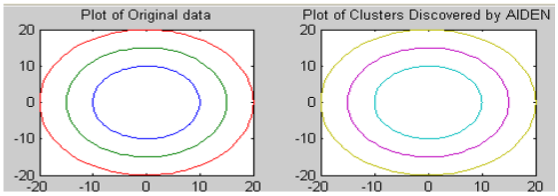

Figure2.b. dataset2. k=10, alpha=15

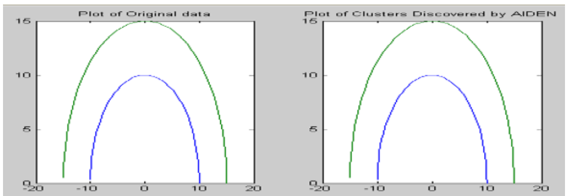

Figure2.c. dataset3. k=8(10), alpha=10(15)

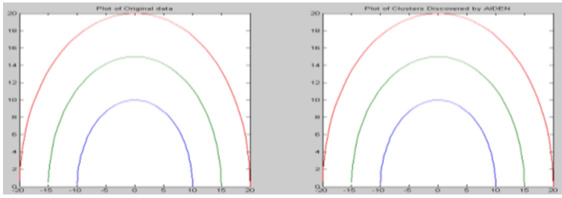

Figure2.d. dataset4. k=10, alpha=15

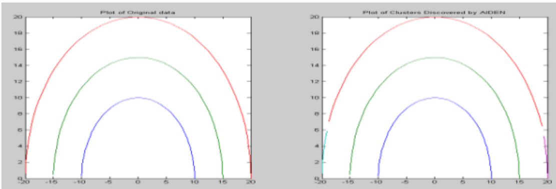

Figure2.e. dataset4. k=14, alpha=15

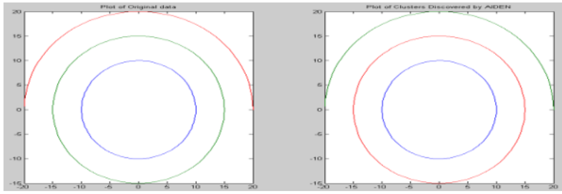

Figure2.f. dataset5. k=10, alpha=24

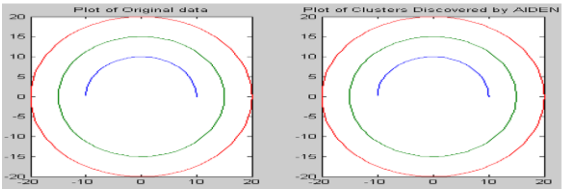

Figure2.g. dataset6. k=8(10), alpha=14(15)

6. Conclusion

The traditional models based on cluster mean as representative of clusters have been sensitive to outliers and parameter initialization. Our model associates a data item (pathogen) with an existing cluster (BCell), only when they are density-attracted to any of the 'dense' elements in the cluster. This property helped in expanding the range of association through recognition by each representative data item (antibody) in non spherical dimension. The strategy of cluster expansion based on *local influence* measure serves the twofold purpose; one, it prevents overfitting; two, it simultaneously assures immunity against outliers. As the algorithm follows a deterministic approach to perform computations for each data point in the input, the convergence of the algorithm is theoretically plausible, and has the same been confirmed with the experimental results. The correct results obtained for different number of patterns convince about scalability of the model. Theoretically the algorithm may be observed to work in a polynomial time. The correct clustering results obtained in presence of both open and closed patterns give a clue towards robustness of the model. A further work is aimed to investigate performance of the model in presence of overlapping patterns. Moreover study toward applicability of the model in relation to clustering and spectral analysis of real world spatial data is planned.

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Design and Development of a Software System for Swarm Intelligence Based Research Studies

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Abstract

This paper introduce a software system including widely-used Swarm Intelligence algorithms or approaches to be used for the related scientific research studies associated with the subject area. The programmatic infrastructure of the system allows working on a fast, easy-to-use, interactive platform to perform Swarm Intelligence based studies in a more effective, efficient and accurate way. In this sense, the system employs all of the necessary controls for the algorithms and it ensures an interactive platform on which computer users can perform studies on a wide spectrum of solution approaches associated with simple and also more advanced problems.

Keywords: Swarm intelligence, artificial intelligence, software system

1. Introduction

Today, the Swarm Intelligence (SI) is a remarkable and important area of the Artificial Intelligence field in the context of the Computer Science. The research scope of this area is associated with the problem-solution approaches on employing the collective behavior of natural or artificial self-organized structures or systems. In this sense, many different types of SI based algorithms have been introduced to provide better solutions for especially real-world based problems. The SI area and its related working scope is very active and newer and more advanced algorithms aiming to provide better approaches rather than the current ones are still designed and developed in a rapid way. As being parallel with the mentioned efforts, there is also be a remarkable need for especially researchers to benefit from tools, programs or general software systems providing solution approaches of the SI based algorithms.

Objective of this paper is to introduce a software system, which employs widely-used Swarm Intelligence algorithms or approaches on a common working environment to be used for the related scientific research studies associated with the subject area. Basically, the system has been designed and developed to provide a typical form-based software environment for the popular and newly developed Swarm Intelligence based algorithms in the mentioned scope. The programmatic infrastructure of the system enables computer users to work on a fast, easy-to-use, interactive platform to perform their studies in a more effective, efficient and accurate way. In this sense, the system employs all of the necessary controls for the algorithms provided and it ensures an interactive platform on which computer users can perform studies on a wide spectrum of solution approaches associated with many types of problems changing from simple to more advanced ones. The author thinks that this software system is a general 'tool box' to be used for SI based research approaches.

The rest of the paper is organized as follows: In the second section, foundations of the software system are described briefly. At this point, some essential references are listed for readers to direct them to have better idea about some SI based algorithms which are included within the designed and developed software system. Next, general design structure and the most important using features and functions of the software system are introduced – explained in the third section. After the third section, a survey work performed among some researchers to have better idea about effectiveness and success of the software system is explained briefly in the fourth section. Finally, results of the realized work and also some future works related to the software system are discussed in the last section.

2. Foundations

The software system designed and developed in this work comes with some popular SI based algorithms to allow working via different kinds of solution based approaches for solving the related problems. In this sense, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Intelligent Water Drops (IWDs) Algorithm and Firefly Algorithm (FA) are included within the software platform. The algorithms have been chosen according to their popularities and / or interesting features in the context of problem solving approaches. In order not to affect flow of the paper and also its readability, readers are directed to some essential references to have more idea about the mentioned algorithms. The related references are listed as below:

- PSO is a global optimization algorithm, which have been introduced by Kennedy and Eberhart [1]. It is based on the simulation of social behaviors appeared in a fish school or bird flock. More information about the PSO can be found in [2 – 4].

- ACO is a SI based algorithm, which have been introduced by Dorigo [5]. Objective of this algorithm is to search for an optimal path in a graph structure by simulating the behavior of ants seeking an appropriate path between the colony and a food source. More information about the ACO can be found in [6 – 8].

- ABC is an optimization algorithm, which have been introduced by Karaboga [9]. Approach of the ABC algorithm is based on the intelligent foraging behavior of a honey-bee swarm. More information about the ABC can be found in [10 – 12].

- IWDs Algorithm is a SI based algorithm, which have been introduced by Shah-Hosseini [13]. Generally, it is similar to the ACO but its working mechanism is based on dynamic of a natural river system. More information about this algorithm can be found in [14 – 16].

- FA is a SI based algorithm, which have been introduced by Yang [17]. Approach of this algorithm is based on flashing behaviors of fireflies. More information about the algorithm can be obtained from [18 – 20].

3. Design and development of a software system for swarm intelligence based research studies

The software system, which has been designed and developed within this study, employs simple and visually improved, form-based controls to ensure the related objectives of the study. At this point; in order to have better idea about design of the system, it is better to examine the programmatic infrastructure of the system before explaining using features and functions.

3.1. Programmatic infrastructure

Basically, the programmatic infrastructure of the software system is based on separate application codes combined within a single software system platform. In this sense, the whole system has been coded over the Microsoft Visual Studio 2010 platform by using the C# programming language. As mentioned before, the system is based on a typical form-based software approach and each application form associated with a specific SI based algorithm includes its own code structure as being independent from other ones and being connected with the main software system interface. Briefly, this infrastructure can be represented in a schema as shown in Fig. 1.

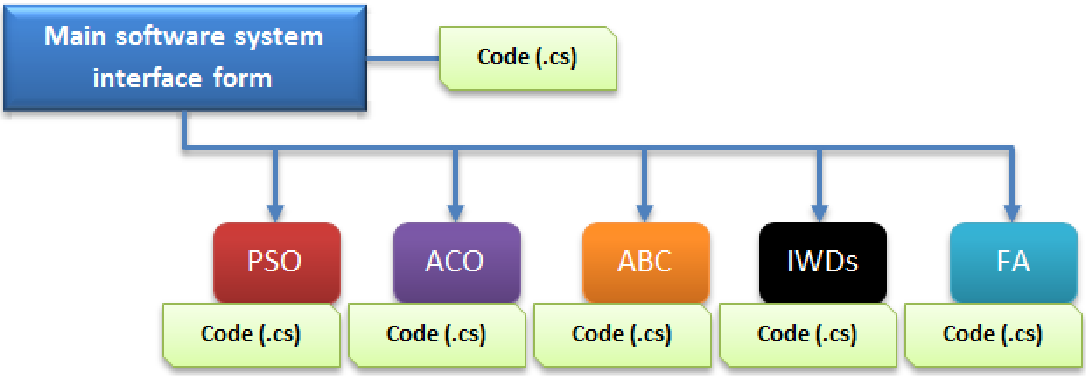

Figure 1. Programmatic infrastructure of the software system

3.2. Using features and functions

Generally, the usage of the developed software system is mostly based on typical form-based controls in order to provide an easy-to-use, fast software environment to improve using experiences positively. In this sense, each algorithm employed in the software system can be reached by using the provided button controls over the main software system interface (form – window). After clicking on the related button, corresponding interface – window of the chosen SI based algorithm is viewed. On a typical algorithm interface – window, it is possible to perform the related operations listed below:

- Defining a new problem and new parameters to perform a solution task associated with the problem scope of the algorithm.

- Opening a saved or predefined problem file to perform newer solution based tasks according to different parameters or structure combinations related to the algorithm (In order to ensure a fast and accurate working mechanism, 'problem files' are saved in the XML file format).

- Performing predefined problems that can be solved by only the related algorithm.

All of the mentioned operations can be performed easily by using the provided controls over the related interfaces – windows of each algorithm. It is also important that each algorithm interface is supported by visual controls to view obtained results with typical iteration-based graphics or problem oriented visual elements. For instance, resulting graph structures are automatically shown by the algorithm interfaces after solving some specific, popular problems like Travelling Salesman Problem (TSP), Vehicle Routing Problem (VCP)…etc. Visually improved using features and functions of the software system are critical aspects to provide more effective and useful platform to perform SI based research studies better.

Related to the designed and developed software system, some screenshots from the software system [interfaces of two algorithms (IWDs and ABC)] are represented in Fig. 2.

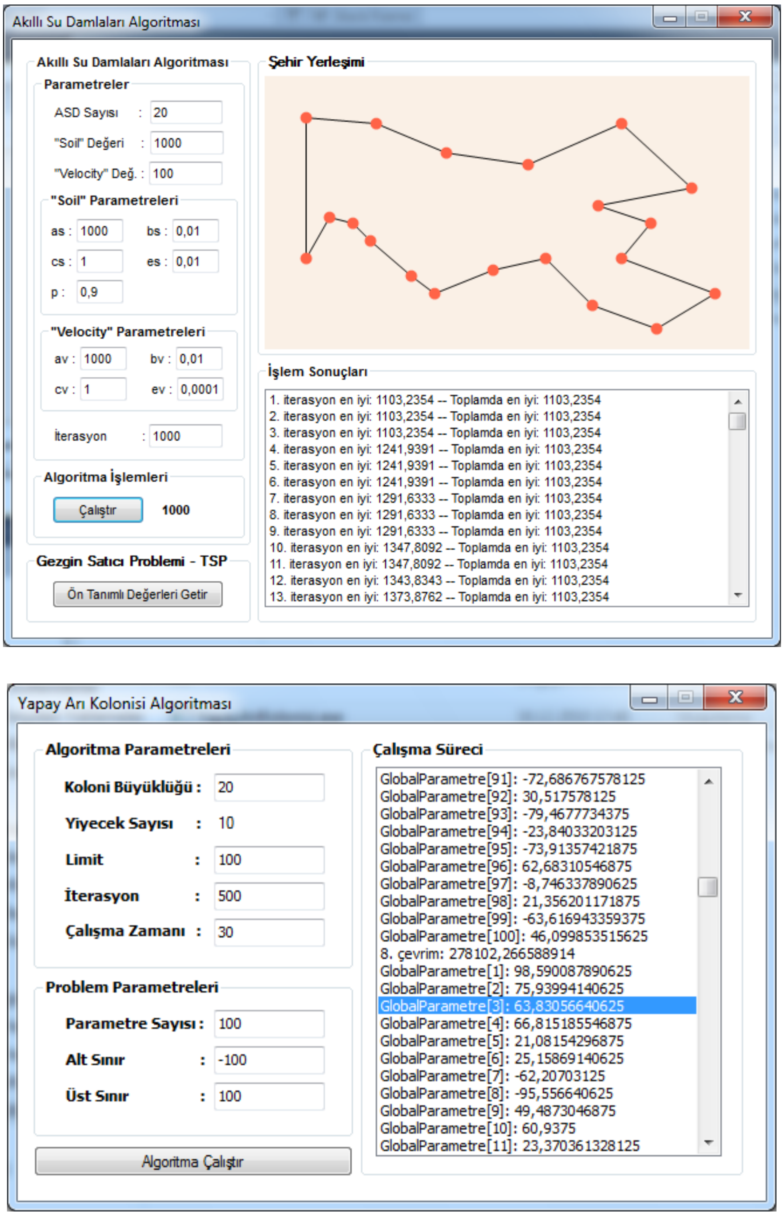

Figure 2. Some screenshots from the software system

4. Evaluation

In order to have more idea about effectiveness and success of the software system, it has been used by a total of 50 different scientists - researchers for two weeks and after the using period, the related scientists - researchers have filled a survey including some statements about the usage and effectiveness of the system. The related survey includes a total of 10 statements that can be evaluated via Likert scale. In this sense, scientists – researchers have typed '1' if they strongly disagree, '2' if they disagree, '3' if they have no clear opinion, '4' if they agree and '5' if they strongly agree with a given statement. The related results obtained with the survey study are shown in Table 1.

Table 1. The survey – evaluation results

Statement	**Number of responses for:**				
	1	**2**	**3**	**4**	**5**
This software system provides a fast research study based platform.	0	0	3	8	39
By using this system, it is easier to perform SI based research studies.	0	0	0	7	43

There must be more SI based algorithms within the software system.	0	0	0	6	44
I didn't like the general characteristic of this software system.	37	10	3	0	0
I liked the scope of the predefined problems for the related algorithms.	0	0	1	6	43
It is hard to perform SI based research studies via this software system.	40	6	4	0	0
I liked the visual controls provided on this software system.	0	0	0	1	49
I don't want to take part in this kind of study process again.	45	4	1	0	0
The system provides an effective approach for SI based res. studies.	0	1	3	6	41
The algorithms provided within the system provide accurate results.	0	0	1	7	42
	Total Respondents: 50				

Results obtained with the survey study show that the software system introduced in this paper is evaluated as an effective and successful platform - environment that can be easily used for performing SI based research studies.

5. Conclusions and future work

The software system introduced in this paper ensures an effective platform, which employs widely-used SI based algorithms on a common working environment to be used for performing related scientific research studies. The system employs fast, simple, easy-to-use controls and interfaces to enable scientists – researchers to perform their works in a more effective, efficient and accurate way. In this sense, the system also provides visually improved controls to improve general using experience. Furthermore, the system also comes with predefined problem files that have been specially prepared for the widely-used algorithms included within the system.

According to the evaluation results, which have been obtained with a simple survey study, all of these mentioned advantages of the system were also confirmed and as general, the software system is evaluated as an effective and successful platform - environment that can be easily used for performing SI based research studies.

In addition to the expressed positive feedbacks, some evaluation results (survey responses) have also encouraged the author to plan some future works. For instance, number of algorithms employed within this system will be increased in future versions by adding different kinds of SI based algorithms. Additionally, future versions of the system will also enable scientists – researchers to reach to the system environment over the Web platform. Finally, there will probably be more visual and interactive controls within the future developments of the software system.

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Data Conflict Resolution among Same Entities in Web of Data

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Abstract

With the growing amount of published RDF datasets on similar domains, data conflict between similar entities (same-as) is becoming a common problem for Web of Data applications. In this paper we propose an algorithm to detect conflict of same properties values of similar entities and select the most accurate value. The proposed algorithm contains two major steps. The first step filters out low ranked datasets using a link analysis technique. The second step calculates and evaluates the focus level of a dataset in a specific domain. Finally, the value of the top ranked dataset is considered. The proposed algorithm is implemented by Java Platform and is evaluated by geographical datasets containing "country" entities.

Keywords: Semantic Web, Linked Data, data conflict, ranking, same entities

1. Introduction

Because of growing amount of data on the Web of data, number of the structured datasets has increased significantly in recent years. Since semantic Web allows machine to process data and retrieve data automatically, availability of high accurate structured data is required. Different datasets are provided by different organization may offer the same contents. For example, WordFactbook and Eurostat datasets overlap deeply, as they both describe country.

According to principle of Linked Data, entities are identified by URI [1]. The same real-word entity can be represented by different URIs correspond to each other with owl:sameAs links. Multiple datasets may provide different values for the same property of an entity [3]. For example datasets such as: DBpedia, Geonames, and WordFactbook publish different information about population of United Kingdom that are mentioned below:

Table 1. United Kingdom different data sets

Geonames	WorldFactbook	DBpedia
60776238	62348447	58789194

However, these data inconsistencies are not acceptable in the cases where quality data is needed, for example in the case of a commercial applications. Generally three different strategies are suggested to deal with such data inconsistency [6]:

- Conflict ignoring: Because data correction is vital in most circumstances, ignorance of data inconsistency is not acceptable in these cases.
- Conflict avoiding: The second strategy handle conflicting data by conflict avoidance. With respect to large dimensions of web of data, this strategy is impossible.

- Conflict resolving: This strategy detects same entities and resolves data conflict between their values. This is the most practical strategy to deal with data inconsistency.

We deal with the inconsistency by resolving data conflict, for this reason, two main approaches are describing here:

- Selection from available data: In this approach a value is selected from inconsistent values. For example, if the population of London is one of the different values (X, Y, Z), one of them must be chosen as the population of London.
- A new value generation: Using this approach a new value is generated using available values. For example, if the population of London is one of the different values (X, Y, Z), the result can be the average value of (X, Y, Z).

Our algorithm resolve data conflict by assigning new value to inconsistent data.

In this paper an algorithm is proposed to detect inconsistency among the same properties' values of sameAs entities in order to choose the most accurate data as output of algorithm. The proposed algorithm is divided into two steps. In the first step datasets are ranked by performing link analysis, then some of them are removed from list of datasets according to their ranks. In the second step the specialty of datasets are computed based on tow metrics: ontology and size of dataset. This paper has been shown that data of the dataset is more special are more accurate. At the end of the ranking the properties' values of top ranked dataset are considered as output.

The proposed algorithm is implemented using Java Platform and evaluated on geographical datasets that contain "country" entity. This paper is organized as follows: In section 2, the related works are presented. The proposed algorithm is described in section 3. The evaluation of proposed algorithm is presented in section 4.Finally conclusion and the outlook on future works are presented in section 5.

2. Related work

Due to novelty of web of data, here are a few researches which have been done to resolve data conflicts in web of data. One of the noticeable researches suggested by Bizer et al Proposes a framework aimed for resolving the inconsistency of data [9]. The main idea of their proposed framework is based on extracting data from different Wikipedia language version and comparing these data with each other to identify the most appropriate language version. For example, despite of better quality of English version as a whole, the population of Germany (as an example of required data) could be indicated more up-to-date in German version than Italian, French or even English version. They provide several strategies to recognize the correct Wikipedia version to choose from. To do this first, data of Wikipedia are converted to RDF format (by DBpedia project) and then they are published in web of data. Because all datasets use Dbpedia ontology, no adaptation is required so Dbpedia ontology is used. Therefore, it's enough to indicate the classes referring to a single entity, using a URI. In other steps, different heuristics are utilized to resolve the inconsistency of data retrieved from different resources. The main purpose of this research is to support the hypothesis that retrieving data from different language versions instead of a single one and combining them to obtain higher quality and more complete data. In this way, the French, Italian, German and English versions of Wikipedia were utilized.

3. The proposed algorithm

This paper provides an algorithm to resolve data conflicts among properties' values of same entities in different datasets. The algorithm works on domain-specific datasets published on a single domain as input and tries to select appropriate values. Figure 1 shows the overflow of algorithm in simple.

3.1. The first step of algorithm

In the first step datasets are published on a single domain are selected then they are ranked by performing link analysis. After finishing this step the low ranked datasets are removed from list of datasets. The Page Rank algorithm is used to rank datasets [14].

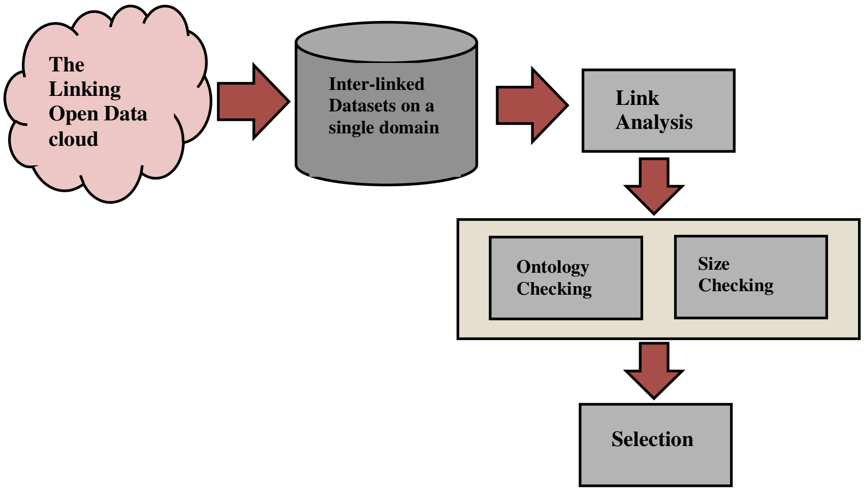

Figure 1. General Workflow of Algorithm

The Page Rank algorithm which is widely used in most search engines such as Google could be easily used to rank linked data. By starting from a point and random surfing, this algorithm evaluates the probability of finding any given page. The algorithm assumes a link between a page i to a page j demonstrates the importance of page j. In addition, the importance of page j is associated to the importance of page i itself and inversely proportional to the number of pages i point to. To adapt this algorithm to web of data, any page considered as a dataset and links between pages considered as links between datasets. According to Page Rank Algorithm, the rank of dataset j in k level is equals to:

$$R^k(j) = \sum_{i \in B(j)} \frac{R^{k-1}(i)}{|L(i)|} \quad (1)$$

Let $B(j) = \{source(l) \mid \forall l \in L, target(l) = j\}$ be the set of datasets point to j and L(i) = $\{$target(l) $\mid \forall l \in L$ $\}$ be the set of datasets linked by a dataset i. the operation is repeated until the algorithm reach to a specific threshold.

3.2. The second step of algorithm

There are several datasets have been published on a specific domain. Some datasets are general so they cover various domains. On the other hand, some datasets cover only specified domain. For example DBpedia is a general dataset covering different entities such as: persons, places, music albums, films etc. while LMDB is a specialized domain-specific dataset on film domain. The idea behind the algorithm is that the domain specific datasets have more accurate data than general datasets. For evaluation of specialty degree of a dataset tow criteria is considered: ontology and size of dataset.

3.2.1. Ontology

Ontology of a dataset should be evaluated to assess the semantic of dataset. As before mentioned, all selected datasets are published on a single domain such as people, place, film, book etc. at first one of the entities that defined in every selected datasets is chosen. Then the words that are semantically similar to chosen entity are extracted. This process is done by WordNet. The result is a list of synonym words. These words should be compared with synonyms list to calculate the counts of words are included in synonyms list. The specialty of ontology can be computed by using following fraction.

$$\frac{|SE|}{|TE|} \quad (2)$$

In this fraction |SE| is the number of entities that is included in synonym words and |TE| is the total number of entities.

3.2.2. Size

Another criterion is size of dataset. It's possible that a dataset be specialized but be small. It is assumed that the dataset is larger is more important and more reliable. So size of the dataset must be considered that is shown in fraction 2.

$$\frac{|ST|}{|TT|} \quad (3)$$

In above fraction |ST| is the number of entities' instances that match with words of synonyms list and |TT| is the number of instances of total entities. Finally combining two fractions 1 and 2 final score can be computed.

$$Score = 0.8 * \frac{|SE|}{|TE|} + 0.2 * \frac{|ST|}{|TT|} \quad (4)$$

4. Evaluation and implementation

The proposed algorithm has been implemented using Java Platform and evaluated via geographical domain datasets. Five major datasets of geographical domain (DBpedia, Geonames, WordFactbook, Eurostat, GeoLinked Data) are used as the input datasets of the proposed algorithm and the output is values of the most accurate data selected from these five datasets. In order to evaluate the proposed algorithm, 35 countries are selected and one property of country entity named population is examined.

In first step, datasets ranks are computed by Page Rank algorithm according link analysis. Result is shown in figure 2.

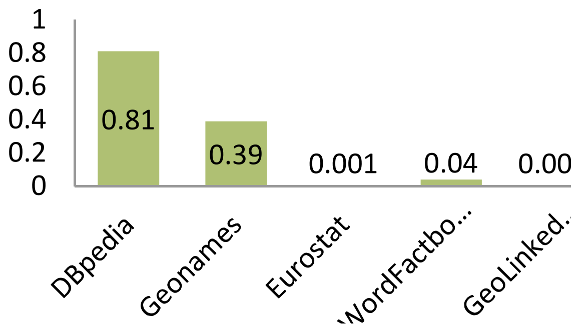

Figure 2. Ranking datasets by Page Rank

As depicted in Figure 2 DBpedia is the top ranked data set while GeoLinked Data and Eurostat are the low ranked data sets. In this stage the data sets whose rank scores are less than half of the rank scores belonging to the top ranked data set are removed from the assessment.

For gathering data we track the links between the remaining two data sets; DBpedia and Geonames. The population of the countries is considered as an attribute for evaluation. Different vocabularies are used in the Web of data. In DBpedia dbpprop:populationCensus and in Geonames gn:population is representative of the population attribute.

Data sets are evaluated based on their ontology and their size. Since the domain that we focused on is geographical data, we chose "country" as the input of WordNet dictionary. Synonyms of "country" are extracted as the output of WordNet. Some of them are land, state, city, fatherland, nation etc. which were named the synonyms list.

In the next step, we extract all entities from the data sets. For example the following SPARQL extracts all entities from DBpedia:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
SELECT distinct ?s WHERE {?s rdf:type owl:Class}
```

Finally we count the entities that contain any words in the synonyms list. The result of first the fraction in equation 4 is shown in figure 3.

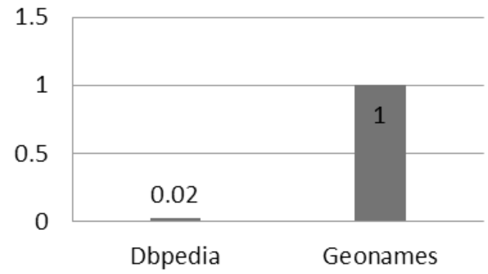

Figure 3. Result of first fraction

In the last stage the size of the data set is examined. The number of instances of specialized entities and total entities are calculated. For example "London" is an instance of a specialized entity. In table 2 one of the properties of "London" is displayed in form of a triple. As is shown, the object of the triple is dbpedia-owl:Place that contains "place" as a member of the specialized entity. And 'A Trip to the Moon' is an instance of non-specialized entity because neither the subject nor the object is in the specialized entities list. After calculating the number of specialized instances and total instances the result of the second fraction of equation 4 is shown in figure 4.

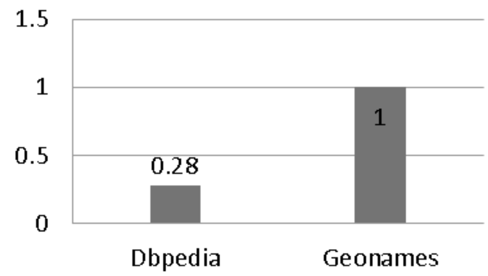

Figure 4. Result of Second Fraction

Finally, the last score with regard to the equation 4 has been calculated and is shown in figure 5. As it shows Geonames gains the highest score. Considering the proposed idea, Geonames' data is the most accurate. So when we are faced with data conflicts, Geonames' data must be chosen.

The WordFactbook is also illustrated in the above table. We can see if WordFactbook is not removed from the synonyms list it would have more accurate data compared with DBpedia data.

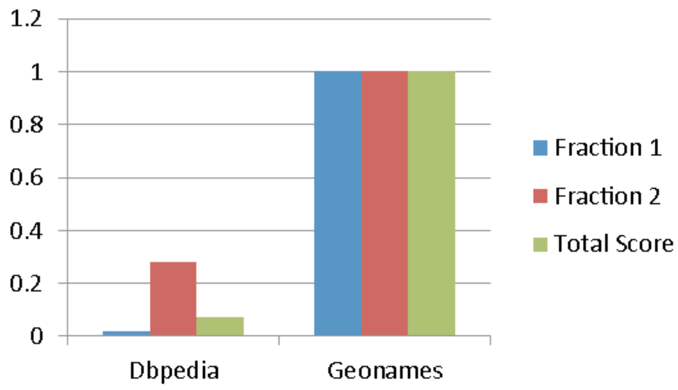

Figure 5. Final Ranking

In order to evaluate our algorithm we found real data on The Population Reference Bureau . The Population Reference Bureau informs people around the world about population, health, and the environment, and empowers them to use that information to advance the well-being of current and future generations. 33 countries were selected for evaluation. The results of our algorithm that are the most accurate values of populations are compared with the data found on The Population Reference Bureau. The numbers of the most accurate data are found on three data sets: WordFactbook, Geonames, DBpedia are shown in following table.

Table 2. The number of most accurate data

WordFactbook	Geonames	DBpedia
7	*22*	*4*

As we know WordFactbook and Geonames are domain-specific data sets on the geographic domain while, DBpedia is a general data set. The results indicate specialized data sets have more accurate data compared with general data sets. The accuracy of the final data set compared with the real data is 67%.

5. Conclusion and future works

This article proposes an algorithm to resolve data conflicts among property values of similar entities in the web of data. The proposed algorithm contains three steps. In the first step, the input data sets published on a single domain are ranked by performing link analysis. In the second step, the recognition of same entities is performed by tracking the sameAs links and vocabulary matching is done manually. In the last stage, the specialty of data sets is computed based on two criteria: ontology and the size of the data set. The proposed algorithm has been evaluated using geographic data sets that contain the "country" entity. Results were compared with real data obtained from The Population Reference Bureau. The data obtained by the proposed algorithm had a 67% matching degree with real data. Future work in relation to this article will focus on:

- Using different domains to evaluate the accuracy of the algorithm.
- Using PageRank algorithm applied on internal entities and intra-links of a data set in order to rank entities.

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AI Reloaded: Objectives, Potentials, and Challenges of the Novel Field of Brain-Like Artificial Intelligence

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Abstract

The general objective of Artificial Intelligence (AI) is to make machines – particularly computers – do things that require intelligence when done by humans. In the last 60 years, AI has significantly progressed and today forms an important part of industry and technology. However, despite the many successes, fundamental questions concerning the creation of human-level intelligence in machines still remain open and will probably not be answerable when continuing on the current, mainly mathematic-algorithmically-guided path of AI. With the novel discipline of Brain-Like Artificial Intelligence, one potential way out of this dilemma has been suggested. Brain-Like AI aims at analyzing and deciphering the working mechanisms of the brain and translating this knowledge into implementable AI architectures with the objective to develop in this way more efficient, flexible, and capable technical systems This article aims at giving a review about this young and still heterogeneous and dynamic research field.

Keywords: Brain-Like Artificial Intelligence, Artificial Brains, Human-Level Machine Intelligence

1. Introduction

The research field of Artificial Intelligence (AI) is concerned with making machines – particularly computers – do things that require intelligence when done by humans. In the 60 years of its existence, it has celebrated dramatic successes and equally dramatic failures. Today, AI has become an important and essential part of technology and industry and provides solutions to some of the most complex problems in computer science. Nevertheless, in terms of its original goal – to create true human-level intelligence in machines – Strong AI has not succeeded yet and perhaps never will. Today, AI researchers are able to create computers that can perform jobs that are difficult for persons like logic, algebra problem solving, path planning, or playing chess. However, they are still struggling with developing a computer that is capable of carrying out tasks that are simple to do for humans like perceiving their environment, assessing complex situations, and taking everyday life decisions. Approaches in the past have mainly concentrated on creating intelligence in computational devices by developing programs that exhibit some kind of "behavior" or "skill" that resembles specific facets of human (or animal) behavior or skills. Investigating the structures, information processing principles, and functions in the brain that lead to the emergence of such behavior and skills was so far generally out of scope of AI technology. For this reason, today's computers and AI programs have simply very little in common with actual brains and minds. Unfortunately, if continuing this mainly mathematically-algorithmically oriented path, any major breakthrough in AI is rather improbable. A paradigm shift might be necessary. With the novel research field of *Brain-Like Artificial Intelligence*, one potential way out of this dilemma has been suggested [111, 137]. However, the discipline of Brain-Like Artificial Intelligence is still not broadly recognized and so far a common research community has not established. Researchers influencing this domain are in fact mostly situated on the borders of other research fields. So far, no standard textbooks or overview articles exist concisely defining the field and explaining the objectives, methodologies, difficulties, etc. Those who want to gain insight into this domain have to laboriously gather up and put together information themselves from bits widely scattered through literature. These circumstances of course do not contribute to an acceleration of the developments in this field. To overcome this problem, this article aims to provide a first comprehensive review on this young domain of science. Although it might happen that certain other researchers of this so far disparate and scattered field will disagree on particular points described in this general overview or claim additional material, such a first draft (or chapter) of a "manifesto" for Brain-Like AI can certainly constitute a basis for fruitful discussions and contribute to further development.

The review starts with a brief discussion of the field of Artificial Intelligence in general and of important current sub-disciplines and their flaws in Chapter 2 in order to better understand the backgrounds that led to the emergence of the domain of Brain-Like Artificial Intelligence. Afterwards, Chapters 3 to 8 focus on the description of the field of Brain-Like Artificial Intelligence. Chapter 3 outlines the basic concept and the general aims of Brain-Like AI. Chapter 4 lists examples of conferences, journals, individual researchers, and research groups that have started to promote and support the idea of brain-inspired AI design. In Chapter 5, a demarcation of the current concepts to artificial neural networks – one of the most prominent ancestors of Brain-Like AI – is made. Afterwards, a classification scheme for approaches so far presented is proposed in Chapter 6. Next, current problems, stumbling blocks, and challenges of the field are summarized in Chapter 7. Last but not least, a route for how to overcome these problems in the future is suggested in Chapter 8.

2. The field of artificial intelligence today and relevant sub-disciplines

„Artificial Intelligence (AI) is the science of making machines do things that would require intelligence if done by humans" [83]. The basic claim of AI is that the central property of (human) intelligence can be precisely described and thus simulated by a machine [78]. Over the last 60 years, AI has changed from a computational discipline into a highly interdisciplinary field incorporating many areas [128]. Artificial Intelligence has given rise to optimism [65, 115], but has also suffered severe setbacks [4, 137]. Today, it constitutes an essential part of technology and industry and is providing solutions to some of the most complex problems in computer science [65]. Although there does not seem to exist a formal, generally accepted definition for Artificial Intelligence, various suggestions for specifying the field of AI (or rather particular sub-domains) have been made over the years. John McCarthy, who introduced the term in 1956 [29], defines it as *„the science and engineering of making intelligent machines"* [78]. More recent AI textbooks describe the domain amongst others as *„the study and design of intelligent agents"* [98] where an intelligent agent is a system that *„perceives its environment and takes actions that maximize its chances of success"* [108]. Today, AI research is highly specialized and deeply divided into sub-domains that have little in common with each other and therefore often fail to communicate [79]. Sub-branches have grown up around the work of individual researchers, particular institutions, the solution of specific problems, the application of widely differing tools, and longstanding differences of opinion about by what methodology AI should or can be achieved. In the following, a suggestion for a classification of these approaches into five different groups is given (Section 2.1) followed by a discussion of the strengths and weaknesses of each group (Section 2.2).

2.1. A possible classification of existing approaches into sub-disciplines

Providing a generally accepted taxonomy for classifying existing approaches into sub-disciplines of AI is not an easy task. Due to the heterogeneity of the field and the overall lack of interchange between groups with different ideologies, there seems to exist more confusion than consensus about this topic. Part of the researchers propose a distinction according to either the particular method used (rule-based systems, neural networks, statistics, fuzzy logics, genetic algorithms, ontologies, etc.) or the application (pattern recognition, optimization, planning, theorem proving, machine vision, language processing, reasoning, etc.). However, in practice, this leads to lists of AI classes easily containing several hundred items. If a researcher does not find an appropriate entry for his/her research, he/she is tempted to introduce a new term, which does not really contribute to a resolution of the categorization problem. Therefore, it is suggested here to better distinguish approaches based to their ideology, methodology, and goal. Accordingly, a classification of the five AI sub-disciplines as described below is proposed, including a description of the core essence of each of these domains. The first three sub-disciplines (Applied Artificial Intelligence, Artificial General Intelligence, and Embodied Artificial Intelligence) are the ones that are the most broadly known today. The further two sub-disciplines (Bio-Inspired Artificial Intelligence and Brain-Like Artificial Intelligence) have been less often explicitly mentioned in literature, are however relevant for this article.

When reading these descriptions, one has to be aware that for Artificial Intelligence in general as well as for the existing sub-disciplines, different, partly not complementary definitions can be found in literature for one and the same term. One example of this are the terms Strong AI and Weak AI, which were originally introduced by J. Searle [110] as part of his Chinese room argument to distinguish between two different hypotheses about Artificial Intelligence. According to the Strong AI hypothesis, a suitably designed computer system can actually replicate aspects of human intelligence and thus have a mind. According to the Weak AI hypothesis, a computer system can (just) simulate aspects of human intelligence and thus (only) act as if it had a mind. This initial usage of those terms is fundamentally different from the way they are widely used today in academic AI research and textbooks. Nowadays, these terms are often rather used to distinguish two particular AI sub-domains (see below) instead of two hypotheses about the achievable goal of AI. Furthermore, one has to be aware that boundaries between the different suggested sub-disciplines can in some cases be a bit blurry. Being able to provide a perfect, unambiguous taxonomy in a field like AI is probably an illusion. It can thus happen that a particular approach could theoretically be assigned to more than one sub-discipline. For instance, a neural network approach could principally be regarded as a bio-inspired (maybe even slightly brain-inspired) approach. If the focus is however rather on employing a “pre-fabricated” network type to solve a very particular task (e.g., the classification of metallic parts of different shapes [133]), it should better be considered as a method of Applied AI. Thus, looking at the objectives, methodology, and followed ideology of a research approach is important for achieving the most adequate categorization.

- **Applied Artificial Intelligence:** One potent sub-field of AI, also referred to as mainstream AI by some authors, is Applied Artificial Intelligence [27] (also called Narrow Artificial Intelligence [46] or Weak Artificial Intelligence [17]). Applied AI is concerned with the use of hardware and software to study or accomplish specific tasks of problem solving or reasoning that do not encompass the complete range of human cognitive abilities or are in most cases even completely outside their focus. Applied AI researchers aim at creating programs that demonstrate “intelligence” in a specialized area such as medical diagnosis, chess playing, algebraic calculation, mathematical theorem-proving, automobile-driving, etc.
- **Artificial General Intelligence:** A second sub-domain of AI is Artificial General Intelligence (AGI) [46]. AGI is not a precisely defined term. P. Wang and B. Goertzel [146] report that in contrast to Applied AI, which aims at particular aspects of applications of intelligence, AGI aims at “intelligence” as a whole, having many aspects and being applied in many situations. R. Koene [61] points out that *“some AGI researchers are explicitly pursuing forms of (general) intelligence designed from first principles and without a desire for comparability or compatibility with human intelligence”*. However, he also states that *“many of the underlying objectives that drive the search for AGI also involve an interest in anthropomorphic interpretations of intelligent behavior”*. In the proceedings of the third International Conference on Artificial General Intelligence in 2010, AGI is described as the research field focusing on the original and ultimate goal of AI – to create broad human-like and trans-human intelligence by exploring all available paths, including theoretical and experimental computer science, cognitive science, neuroscience, and innovative interdisciplinary methodologies [12]. Some researchers place the term AGI today more or

less on a level with the term Strong Artificial Intelligence [27]. In contrast to its original use, Strong AI now refers to the design of machines of human intelligence level, i.e., machines that can successfully perform any intellectual task a human being can do [65]. C. Pennachin and B. Goertzel [94] point out that the term Artificial General Intelligence (AGI) was introduced in order to avoid the connotations "human-level" or "human-like"' of the term Strong AI, which were widely used before, and to further allow the inclusion of non-human models.

- **Embodied Artificial Intelligence:** A third important sub-discipline of AI is Embodied Artificial Intelligence [97] (also called Embodied Intelligence [18], New Artificial Intelligence [87], Behavior-Based Artificial Intelligence [76], or Nouvelle Artificial Intelligence [96]). The goal of Embodied Artificial Intelligence is to study *"how intelligence emerges as a result of sensorimotor activity, constrained by the physical body and mental developmental program"* [127]. Accordingly, the field of embodied intelligence is strongly connected to the design of "intelligent" agents that perceive their environment and take actions that maximize their chances of success [108].
- **Bio-Inspired Artificial Intelligence:** Another sub-discipline of AI is the field of Bio-Inspired Artificial Intelligence [39] (also mentioned in correlation with Biologically-Inspired Artificial Intelligence [25], Naturally-Inspired Artificial Intelligence [13], Bionics [132], and Artificial Life [14]). Bio-Inspired Artificial Intelligence focuses on the design of intelligent machines by taking inspiration from biology. J. Chappell et al. [24] point out that this includes *"(1) attempts to mimic details of the morphology and behavior of humans or other animals; (2) attempts to apply theories about how neural or evolutionary mechanisms work, to solve engineering problems; (3) applying techniques inspired by social behaviors of organisms, including swarming, flocking, use of pheromone trails, etc.; (4) attempts to understand the problems solved by biological evolution in order to clarify goals and requirements for AI/robotics."*
- **Brain-Like Artificial Intelligence:** A further emerging sub-domain of AI holding great promises and being subject of this article is the field of Brain-Like Artificial Intelligence [41, 111] (also called Brain-Inspired Artificial Intelligence [137]). Brain-Like Artificial Intelligence – a term that is currently being established [111] – is concerned with investigating how the human (or animal) brain is structured and how it functions with the aim to emulate these concepts for the design of more efficient, effective, and "intelligent" technical systems [137, 73].

2.2. Weak points of current sub-disciplines

In the approximately 60 years since its development and implementation, research in Artificial Intelligence has produced many useful outputs in terms of solved technical problems and has also contributed insights to our understanding of the "nature of intelligence". Nevertheless, the overall challenge of developing "truly intelligent machines" applicable for all kinds of tasks that can be solved by humans is enormous and much remains to be done to overcome it. Different sub-disciplines of AI have targeted this challenge from different perspectives. Brilliant researchers can be found in each of them. Nevertheless, each field today still shows certain "intrinsic" weak points. An attempt to identify and describe them is made in the following.

Applied Artificial Intelligence

Although there exist initiatives to encourage people to focus on the advancement of the scientific understanding of cognitive systems[1], researchers today choose to focus for the most part on Applied AI [94], i.e., specific sub-problems such as data mining, computer vision, logistics, speech recognition, medical diagnostics, banking software, industrial robotics, search engines, etc.,

[1] http://www.socsci.ru.nl/CogSys2/PDFs/Cogsys2_Opening_by_Colette_Maloney.pdf

where they can produce commercial applications and verifiable results [90, 108]. Applied AI can therefore be considered as AI mainstream research direction. Some of the methods and programs developed in this context are extremely successful in what they do [94]. Some AI researchers today still hope that more general purpose AI systems can emerge by combining the programs that solve various sub-problems using an integrated subsumption architecture, agent architecture, or cognitive architecture [44, 86]. However, the success of achieving a general level of intelligence by such "superposition approaches" is heavily doubted by other AI researchers. In an interview in Hal's Legacy in 2000, M. Minsky, one of the pioneers and co-founders of AI, pointed out that *"we really haven't progressed too far toward a truly intelligent machine. We have collections of dumb specialists in small domains; the true majesty of general intelligence still awaits our attack. We have got to get back to the deepest questions of AI and general intelligence and quit wasting time on little projects that don't contribute to the main goal."* [45]

Artificial General Intelligence

Excessive optimism in the 1950s and 1960s concerning Artificial General Intelligence – although at this time this name was not used – has given way to the recognition of the extreme difficulty of creating human-level intelligence, which is today considered as the possibly hardest problem that science has ever undertaken. Thus, in the following decades, most AI researchers have devoted little attention to Artificial General Intelligence. Nevertheless, today, a small number of scientists are active in AGI research. The research is extremely diverse and frequently pioneering in nature. Estimates of the time needed before a truly flexible AGI system could be built, if at all, vary from a decade to over a century [94]. R. Kurzweil and colleagues point out that a timeframe between 2015 and 2056 is plausible [65]. However, many AI researchers of other sub-disciplines are not at all convinced that progress will be that fast. Critics doubt whether research in the next decades will even produce a system with the overall intellectual ability of an ant [27].

Embodied Artificial Intelligence

While Applied AI and Artificial General Intelligence have been centered round the idea of the computational representation of the world, the approach of Embodied AI is centered around action in the world. Embodied Intelligence suggests that the basic assumption of traditional AI, according to which cognition is equal to computation, is not adequate and needs to be reconsidered. When the digital computer was invented, many felt that the core and essence of thinking and intelligence had been found. Computers were considered "electronic brains" in those days and the human mind was viewed as a computer [96]. In the 1980s and 1990s, a subset of researchers from Artificial Intelligence, psychology, cognitive science, and brain science eventually realized that the idea of computers as intelligent machines, at least in the form they exist today, was misguided. They concluded that the brain does not run "programs" and has not evolved to perform mathematical proofs[2] but to control behavior that ensures the organism's survival in the real world [96]. Accordingly, they further concluded that intelligence needs a body equipped with sensors and actuators and an environment on which to act. Based on this claim, a new sub-discipline of AI evolved: the field of Embodied Artificial Intelligence [18]. Embodied Intelligence has moved its focus away from computers and towards more interactive systems such as robots or ubiquitous environments equipped with many sensors and actuators. It focuses not necessarily on human intelligence but rather on non-human biological systems such as insects [97]. Important research areas in Embodied AI today include walking, locomotion, low-level sensory-motor intelligence, orientation behavior, path-finding, elementary behaviors such as following and obstacle avoidance, etc. [97].

[2] In this context it should be mentioned that other researchers partly disagree, as certain animals and particularly humans need cognitive capabilities that allow for planning (acting-as-if), for instance, in order to cope with dangerous situations where a solution cannot be worked out by trial and error as this would most likely result in getting injured or killed [28,125].

Although usually not directly related to each other in scientific literature [92], Embodied Artificial Intelligence seems to have much in common with the domain of Cybernetics [57], which already emerged approximately a decade before the field of AI was founded [149]. Cybernetics was particularly interested in the question of how *"animals and humans maintained equilibrium within, and responded appropriately to, their ever-changing environment"* [70].

Today, the field of Embodied Artificial Intelligence is still highly diverse and far from being theoretically stable [97]. Interestingly, many researchers of Embodied Intelligence do not refer to themselves as working in Artificial Intelligence but rather in robotics, engineering of adaptive systems, artificial life, adaptive locomotion, bio-inspired systems, and neuroinformatics [97]. In Embodied AI, the identification of the fact that natural intelligent systems are all biological and have to perceive and interact with their environment was without a doubt an important step. However, unfortunately, this approach offered new pitfalls. One essential criticism of Embodied AI is that the slogans of embodiment encouraged researchers to focus exclusively on "on-line" interaction of robots with the environment (see for example [101]) without "reflecting" about their activities (e.g., to consider what they did before, why they did it, what would have happened if they had not done it, whether they should try something different next time, etc.). R. Pfeifer and F. Iida [97] point out that *"to date, most robots are specialized, either for walking or other kinds of locomotion purposes, or for sensory-motor manipulation, but rarely are they skilled at performing a wide spectrum of tasks. One of the fundamental unresolved problems has been and still is how thinking emerges from an embodied system. Proactively speaking, the central issue could be captured by the question: How does walking relate to thinking?"* Thus, what happened in the field of Embodied AI was that most researchers failed to consider "disconnected" cognition not directly involving sensorimotor coordination as much as researchers in earlier AI failed to consider "connected" (online) cognition, though there was more justification for the omissions in the early days of AI due to still inadequate technology. In this context, A. Sloman [124] mentions that *"the tautology that a robot that acts and perceives in the world must be embodied is often combined with false premises, such as the premise that a particular type of body is a requirement for intelligence, or for human intelligence, or the premise that all cognition is concerned with sensorimotor interactions, or the premises that all cognition is implemented in a dynamical system closely coupled with sensors and effectors"*. He further criticizes that *"robots so far produced by „nouvelle AI" are pre-constructed and typically move around rather pointlessly (possibly doing something useful as a side-effect), or achieve arbitrary goals imposed from outside, as opposed to doing what is required to grow, maintain, or reproduce themselves"*. J. Starzyk [128] points out that *"Embodied Intelligence revived the field of autonomous robots, but as robotics thrived, research on Embodied Intelligence started to concentrate on the commercial aspects of robots with a lot of effort spent on embodiment and a little on intelligence. Researchers today concentrate on advancements of robotic technology like building artificial skin and muscles. While this might be relevant for the development of robots, it diverts attention from developing intelligence. Furthermore, currently, process efficiency dominates over generality. It is more cost efficient and cheaper to design a robot for a specific task than one that can perform various tasks, and most certainly even more than one that can actually make its own decision"*.

Bio-Inspired Artificial Intelligence

Parallel to the emergence of Embodied Intelligence, more attention also started to be directed towards the derivation of biological concepts [97]. While Artificial Intelligence has traditionally focused on the computational reproduction of the behavior and abilities of humans, Bio-Inspired AI takes inspirations from a wider range of biological structures that show the capability of adaptation and autonomous self-organization. N. Forbes [38] describes the focus of the field to be on *"the use of biology in algorithm construction, the study of how biological systems communicate and process information, and the development of information processing systems that use biological materials, are based on biological models, or both"*. As outlined in [39, 75, 11], Bio-Inspired AI envisions amongst others evolutionary computation, evolutionary electronics, biologically inspired hardware, bioelectronics, amorphous computing, artificial immune systems, genetic algorithms, DNA computation, cellular automata, biomolecular self-assembly, artificial neural networks, biorobotics, and swarm intelligence. In the book *"Bio-Inspired Artificial Intelligence – Theories, Methods, and Technologies"*, D. Charles et al. [25] categorize Biologically-Inspired approaches to AI into 7 groups: evolutionary systems, cellular systems, neural systems, developmental systems, immune systems, behavioral systems, and collective systems. Like Embodied AI, Bio-Inspired AI also has some common roots with the field of Cybernetics, which is interested in human and animal nervous systems [70]. However, the central aim of Cybernetics is the understanding with less emphasis on the construction of useful artifacts. Without doubt, Bio-Inspired AI and bio-inspired technology have great potential. However, approaches suggested in this field are of great diversity, which makes it difficult to provide an analysis of the strengths and flaws of this domain with general validity. While some approaches like artificial neural networks and genetic algorithms are already well established methods that find application in various areas, many others are still on the level of very basic research and concept clarification. Bio-Inspired AI is not yet widely considered as an own, separate research field, but rather it summarizes biologically-inspired approaches introduced in diverse other disciplines. In general, the term "bio-inspired" implies that inspiration for technical development is taken from nature. However, the level of abstraction at which nature serves as archetype varies greatly. Part of the approaches currently consider and investigate information processing and computational principles occurring in nature while others analyze biological organisms on a behavioral level or take nature more as a metaphor than as a model [38]. In the latter context, B. Sendhoff et al. [111] criticize that so far, the contribution of so called "Bio-Inspired" AI approaches to a better understanding of "biological intelligence" and "brain intelligence" has been very limited. Similar as in classical AI, there exist a number of approaches that have resulted from a symbiotic cooperation between engineers, computer scientists, and researchers from life sciences. However, a significant number of models are still developed by researchers from the technical science discipline only. A. Schierwagen [109] comments that in practice, this has sometimes led to so-called bio-inspired technologies that take advantages of fancy biological names as selling arguments without an in-depth exploitation of biological principles.

Artificial Intelligence as a Whole

In summary, it can be concluded that throughout its history, Artificial Intelligence has always been a topic of much controversy [29, 90]. Taking inventory today, Artificial Intelligence can achieve good solutions that can compete with or exceed human (or at least higher developed animal) cognitive abilities and skills for problems that are sufficiently well structured and whose complexity can be controlled. Today's AI systems particularly outperform humans in jobs that are of an "abstract nature" like logic, solving puzzles and algebra problems, path planning, playing chess, etc. and that can be well described in a mathematic or algorithmic form and thus be relatively easily implemented computationally (see also [97]). Certain problems have these characteristics. However, natural environments do not [111]. AI researchers have so far struggled to develop computational systems that are capable of carrying out tasks that are simple and "natural" for humans, e.g., perception in the real world, object manipulation, sensory-motor coordination, locomotion, common sense, evaluating complex situations, making decisions in real world situations, everyday natural language, etc. [96, 137]. J. Starzyk [128] criticizes that Artificial Intelligence often applies the principle of chip design to create a system with no intelligence and call it intelligent as long as it does its job. During its history, Artificial Intelligence challenges have experienced a revival in various disciplines related to AI, e.g., computational intelligence [98], cognitive automation [129], cognitive computation [55], and cognitive robotics [26]. However, the basic aims and difficulties have remained mainly intact.

Despite the many successes of Artificial Intelligence, fundamental problems of intelligence are still unanswered today [128]. As B. Sendhoff et al. [111, 112] point out: *"Superior functionality* *in a single problem domain can often already be achieved by specialized technological systems (thinking about a simple calculator or a chess program), however, no technological system can robustly cope with the plethora of tasks encountered by any* (higher developed) *animal during its life time. We have to acknowledge that in spite of its tremendous advances in areas like neural networks, computational and artificial intelligence, and fuzzy systems, existing approaches are still not able to mimic even for instance the lower-level sensory capabilities of humans or animals."*

Thus, the open question remains: *How to continue on the path to machine intelligence for the problem domains that cannot yet be handled with existing approaches?* An emerging path that – if followed wisely – could hold a solution to this question is the field of *Brain-Like Artificial Intelligence*.

3. The basic concept and aims of Brain-Like Artificial Intelligence

3.1. Basic concept

As outlined in Section 2.2, Artificial Intelligence today mainly provides methods and tools to automate specific, well-structured tasks that take place in environments of limited complexity. For tasks that show these characteristics, technical systems can compete with or even surpass human performance. However, there does not currently exist a technical system that can even come close to competing with the overall capacity and the capabilities of the human mind. The same holds true for perceptual, motor control, and other cognitive abilities of higher developed animals. In order to substantially progress further a paradigm shift might be necessary in this field. With Brain-Like AI, a potential way out of the current AI dilemma has been proposed. Its basic idea is highly intuitive [35, 95, 99, 135]: *use the brain as archetype for AI model development!* However – considering the last 60 years of AI history – it is quite clear that it has so far not been that easy to implement this idea properly (see also Chapter 7).

One difficulty with current approaches in Brain-Like Artificial Intelligence is, as it can also be observed in other sub-disciplines of AI, that different researchers have partly divergent opinions on what Brain-Like Artificial Intelligence actually is and how it should be done (see also Chapter 7). In the book *Creating Brain-Like Intelligence: From Basic Principles to Complex Intelligent Systems*, B. Sendhoff et al. [111] point out: *"As the name suggests, we would like to achieve intelligence as demonstrated by brains preferably those of highly evolved creatures."* Although part of the contributions presented in this book actually aim at investigating and emulating the structures, information processing principles, and functioning of the brain that lead to the emergence of certain skills and abilities, it is left open if an analogy to the brain is sufficient in terms of externally emitted functions or if it should also be in terms of internal processes and principles. However, if limiting the similarity to emitted functions, no clear demarcation line to the other fields of AI discussed in Section 2 – particularly to AGI – can be drawn. Brain-Like Artificial Intelligence as understood in this article therefore refers to both similarity in internal brain processes and principles and their emitted function. While principally the brain of different higher developed organisms could be analyzed for this purpose (see also Section 6.1), the focus is on the human brain in this article. Accordingly, the "basic dogma" of Brain-Like Artificial Intelligence as used here is the following:

"Basic Dogma" of Brain-Like Artificial Intelligence as Used Here
It is well appreciated that the human brain is the most sophisticated, powerful, efficient, effective, flexible and intelligent information processing system known. Therefore, the functioning of the human brain, its structural organization, and information processing principles should be used as archetype for designing artificial intelligent systems instead of just emulating its behavior in a black box manner. To achieve this, approaches should not build on work from engineers only but on a close cooperation between engineers and brain scientists.

Acknowledging the simplicity, clarity, and intuitive logic of this basic dogma, the question arises why such a brain-like approach to AI has not already been followed more intensively from the very beginning of the field of AI. One main reason for this is that 60 years ago, when the domain of AI started to evolve, the available body of knowledge about the functioning of the brain was still very limited. Apart from simple nerve cell models, the brain could merely be considered as a black box system of which only the external behavior could be observed and studied. The development of new measuring and imaging techniques in the last decades has shed new light on the internal structures, information processing principles, and functioning of the brain. In this context, B. Goertzel [45] states: *"Prior to the last few decades, the traditional disciplines of psychology and neuroscience offered extremely little to AI designers. Since the emergence of cognitive science and cognitive neuroscience, things have gotten a little better."* It might now be time to start using and extending this acquired knowledge by translating it to functioning and technically implementable models.

3.2. Basic aims

In simple words, the research field of Brain-Like AI is concerned with the development and implementation of concepts and models of the human (or animal) brain and their application in various kinds of technical systems and domains. The motivation for research in Brain-Like AI is twofold and outlined in the following [41, 48, 99]:

- On the one hand, these models and their implementation shall in the future lead to better information processing, computation, and automation systems. Domains which are eagerly waiting for such novel "intelligent" approaches in order to deal with their upcoming needs are, amongst others, the field of machine perception [130, 138], sensor fusion [135], ambient intelligence [19], interactive systems [20, 140], smart buildings [67, 136, 139], automation [143], robotics [22, 32, 33], agent technologies [68], information processing [50, 131], computation [6, 142], and web intelligence [151].
- On the other hand, the models shall contribute to a better understanding of the human (or animal) brain. When trying to technically implement models of the brain, unknown points cannot just be left open without even mentioning them as the developed machine has to be able to perform certain functions. Therefore, this emulation process is an important means to detect weak points and inconsistencies in current brain theories and to contribute to the development of new brain theories [82, 138, 141, 144].

Of course, each researcher will place their particular focus in terms of these two basic motivations. While some concentrate on topics of the first point, others may emphasize the second.

4. Support from the scientific community

Although still being a heterogeneous and emerging discipline, the principal idea of brain-inspired approaches to solutions in AI is today well supported by numerous researchers. N. Zhoung [151] points out that *"AI research has not produced major breakthrough recently due to a lack of understanding of human brains and natural intelligence."* He predicts that the next major advancements in AI will most likely result *"by an in-depth understanding of human intelligence and its application in the design and implementation of systems with human-level intelligence"*. M. Minsky suggests that findings about how natural intelligence (particularly the brain) works have to be the basis for developing concepts for technical approaches trying to achieve intelligence [134]. J. Kirchmar and G. Edelman [63] state that *"the analogy to the natural brain must be taken serious"* [112]. C. Pennachin and B. Goertzel [94] comment that *"one almost sure way to create Artificial General Intelligence would be to exactly copy the human brain"*. C. Goerick [42] discusses: *"We would like to create brain-like intelligent systems, hence we have to understand how the brain works. The artifacts we are creating should show what we have understood from the brain so far,* *and should help formulating the next questions aiming for further understanding the brain."* R. Koene [61] indicates that *"the brain's implementation is not necessarily the best one according to criteria used to measure performance at solving a particular problem, but at least it is an existing implementation, and we have some idea of the specifications that it meets"*. D. Dietrich and his team emphasize that one way to solve the dilemma of AI and automation in general is the application of bionic approaches, particularly of approaches considering the human brain and mind. They recommend a close cooperation between engineers and brain scientists for this purpose [21, 35, 68, 91, 100, 104, 134, 150]. J. Hawkins [51] states that *"brains are totally unlike the relatively simple structures of even the most complex computer chip"* and that therefore *"the way we build computers today won't take us down the path to create truly intelligent machines."* S. Potter [99] points out that *"yet, little attention in the AI field has been directed toward actual brains."* He illustrates that *"the human brain is the best example of intelligence known, with unsurpassed ability for complex, real-time interaction with a dynamic world"* and concludes that *"if AI were to become less artificial, more brain-like, it might come closer to accomplishing the feats routinely carried out by natural intelligence*." S. Amari [6] indicates that *"the more is known about the functionality of the brain the more intelligent the information systems will become"*. B. Goertzel [45] points out that *"we have a great deal of respect for the fact that the human brain/mind actually exists and functions, so it would be foolish not to learn from it all that we can."*

Within the last few years, the first conferences and workshops promoting the topic of Brain-Like AI have taken place, e.g., the *Engineering-Neuro-Psychoanalysis Forum* (2007)[3], the *Brain-Inspired Cognitive Systems Conference* (2004–2012)[4], the *Conference on Brain-Inspired Information Technology* (2006)[5], the *International Symposium on Creating Brain-Like Intelligence* (2007)[6], the *International Conference on Brain Informatics* (2009–2012)[7], the *AAAI Spring Symposium* (2006)[8] with the title *Between a Rock and a Hard Place: Cognitive Science Principles Meet AI-Hard Problems*, and the *International Conference on Artificial Neural Networks* (2011)[9] with focus on *Machine Learning re-inspired by Brain and Cognition*. Other conferences have dedicated tracks and special sessions to this topic, e.g., the *INDIN* (2008–2010)[10] on *Cognitive and Computational Intelligence in Industrial Informatics*, the *HIS* (2010) on *Modeling the Mind*[11], and the *Africon* (2011)[12] on *Challenges in Autonomic Systems looking for New Bionic Approaches for Modeling the Mind*.

Similarly, some pioneer journals have started to deal with topics of Brain-Like AI like the journal of *Broad Research on Artificial Intelligence and Neuroscience*[13] or the special issue on *Brain-Inspired Cognitive Agents* of the *ACM Transactions on Intelligent Systems and Technology*[14].

Moreover, the first books have been published promoting the topic of "brain-inspiredness". Among these are the books *Simulating the Mind: A Technical Neuropsychoanalytical Approach* [35], *Creating Brain-Like Intelligence: From Basic Principles to Complex Intelligent Systems* [111], and *Brain-Like Computing and Intelligent Information Systems* [6].

[3] http://www.indin2007.org/enf/index.php
[4] http://www.conscious-robots.com/en/publications/conferences/bics-2010.-brain-inspired-cognitive-systems-confe.html
[5] http://www.elsevier.com/wps/find/bookdescription.authors/712521/description
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[13] http://www.edusoft.ro/brain/index.php/brain
[14] http://tist.acm.org/CFPs/TIST-SI-BICA-10.pdf

5. Artificial neural networks – the ancestors of Brain-like AI?

When claiming that Brain-Like Artificial Intelligence is a novel and recent research field, one question that will most certainly pop up is: "Is the concept really that new?" The next question that is most likely to follow is: "What about artificial neural networks?" These are justified questions, which will be considered in more detail in the following.

In principle, the drive to study and emulate the functions of the (human) brain might date back thousands of years. However, only with the development of modern day electronics have attempts to emulate the brain and thinking processes become more tangible. In the 1940s, the area of neural network research began to emerge [52, 80]. Since then, artificial neural network (ANN) research has gone through various highs and lows. Today, artificial neural networks are used for pattern recognition, classification, and prediction. Without doubt, ANNs are useful tools and have brought solutions to various problems that are difficult to solve with conventional computers. However, they have yet failed to produce any kind of behavior that could be considered truly intelligent. Several researchers, for instance H. De Garis [31], claimed that this is due to the fact that current networks were just too small in terms of number of used neurons. However, this explanation is most likely insufficient. I. Aleksander [3] indicates: *"The point is that these puzzles are not puzzles because our neural models are not large enough."* Although ANNs have often been viewed as simplified models of neural processing in the brain, today their relation to biological brain architectures is questionable. In fact, artificial neural networks do contain some neuron-like attributes (connection strengths, inhibition/excitation, etc.) but they overlook many other factors, which may be significant to the brain's functioning [103]. J. Hawkins argues that artificial neural network research ignores essential properties of the (human) cortex and instead prefers to focus on simple models that have been successful at solving simple problems [51]. More specifically, up to today, artificial neural networks have mainly been an attempt to emulate processing aspects of individual biological neurons, not of whole neural brain networks and not of learning principles in such biological networks. Unlike brains that seem to have already a great deal of organization present even during fetal development, ANNs generally start from a jumbled, randomized set of connection strengths [103]. The methods for achieving networking through learning in ANNs are based mainly on mathematical models, not on biological ones.

Accordingly, the question to what extent ANNs are actually brain-inspired can be answered as follows. Artificial neural networks, as they exist today, are systems that are loosely patterned on the nervous system. Their basic processing elements can be considered to be brain-inspired (or better neuron-inspired) and the principal idea to put them together to form networks. However, the rest of the framework, i.e., the way how artificial neurons are structured into networks, how their interconnections are determined through learning processes, etc. is based on mere mathematical assumptions. Therefore, it is suggested here that artificial neural networks should rather be classified as an approach of Bio-Inspired AI or even Applied AI than one of Brain-Like AI. Without question, the initial idea behind ANNs is brilliant and it is astonishing how many tasks can today be solved with them. Unfortunately, these promising results in some areas were probably also the reason that have led a number of researchers to come to the inappropriate conclusion that ANNs as they exist today have much in common with brains. In fact, their success has to be mainly attributed to the mathematical theory behind them and not to biological similarities with the brain. Nevertheless, it is not impossible that in the future, further developments in this field based on novel and extended insights from brain research will lead to neural network structures that are actually worthy to be called "brain-like".

6. Possible classifications of Brain-like AI approaches

As outlined before, the principal idea behind Brain-Like Artificial Intelligence has existed for several decades. However, so far, many stumbling blocks and detours had to be taken concerning its implementation. Thus, Brain-Inspired Artificial Intelligence can still be considered a quite novel, dynamic, and heterogeneous field. Different researchers have different opinions regarding by what means and how closely one needs to simulate the brain in order to achieve brain-like behavior [73].

On the one extreme, there are AI approaches that are based purely on abstract mathematical theories of intelligence and do not draw any mapping between natural and artificial cognition at any level. Such approaches, which rest on the assumption of vast levels of computing power greater than anything that will be physically possible in a foreseeable future, have clearly nothing to do with Brain-Inspired Artificial Intelligence as described and defined in this article.

On the other extreme, there are claims, e.g., by R. Kurzweil [64], that the most effective path to Strong AI is to reverse-engineer the human brain to a level as precise as necessary to replicate its function. In practice, this has led to "brain simulations" aiming at a level of precision as detailed as the cellular level – e.g., in the Blue Brain project [77] – or even the molecular level – as in the Cajal Blue Brain project[15].

In sum, regardless of the level of detail of simulation, most approaches suggested so far should be considered as rather loosely brain-like models [41]. Looking at the great variety of existing approaches, finding a good classification scheme for them is not an easy task and category boundaries generally remain vague. Nevertheless, in the following sub-sections, several possible ways for a classification are suggested.

6.1. Biological organism used as blueprint

Traditionally, Artificial Intelligence has focused its attention mainly on the cognitive abilities of humans. The roots for this go back as far as to R. Descartes who stated that only humans are capable of thought. He considered animal behavior as a series of unthinking mechanical responses to stimuli that originate from the animal's internal or external environment [59]. In contrast, many researchers today disagree with this view – at least for higher developed animals. For instance H. Terrace [15] claims that *"animals do think but cannot master language"*. A. Sloman goes even further and attributes animals with some kind of mathematical competences. Specifically, his research interests are related to the biological basis of mathematical competence in humans and creative problem solving in other animals [126]. S. Kak [59] points out that *"as other animals learn concepts nonverbally, it is hard for humans, as verbal animals, to determine their concepts"*.

Based on these facts, Brain-Like Artificial Intelligence aiming at the emulation of brain functions cannot only take inspiration from the human brain but principally also from brain architectures of all kinds of higher developed animals. Thus, the biological species which is taken as inspiration for the blueprint of a brain-like architecture constitutes one possible way of classification. Prominent species for such brain and behavior models have so far ranged from elephants, cats, cheetahs, deer, primates, and squirrels over crows, pigeons, and parrots to octopuses and insects. Nevertheless, as A. Sloman pointed out in a private discussion with him, one has to be aware that no matter which organism's brain we take as archetype, we cannot avoid explicitly or implicitly focusing on human brains, or at least their competences. After all, we have (at least initially) to use human ways of thinking when we ask what other organisms can and cannot do.

6.2. Bottom-up versus top-down design

Another possibility of categorization is – similar as also in mainstream AI – a division into bottom-up (neural) models and top-down (symbolic) models [27]. Generally, in top-down AI, cognition is treated as a high-level phenomenon that is independent of the low-level details of the implementing mechanism. Researchers in bottom-up AI take an opposite approach and simulate networks of neurons. They then investigate what aspects of cognition can be recreated in these networks.

[15] http://cajalbbp.cesvima.upm.es/

6.3. Involved discipline of brain science

A further method of classification would be the discipline of brain science that served as the inspiration for the technical model. Disciplines today involved in this task range from neuroscience over psychology and pedagogics to psychoanalysis. While neuroscience can be considered as a "bottom-level" approach, the further disciplines target the problem of creating Artificial Intelligence from a "top-level" perspective. Furthermore, in the last decades, disciplines started to emerge, which aim at investigating both top and bottom-level aspects of cognition and particularly their correlations. Amongst these are neuro-psychology, neuro-psychoanalysis, and cognitive neuroscience.

Although the methodology of classification based on the underlying brain theory would make sense, it does not seem to have yet found its way into scientific literature. One problem with this kind of classification might certainly be that today, the content and borders of each of these disciplines of brain sciences and cognitive sciences are not clearly defined. Each discipline is again split into further sub-disciplines, which show partial overlap but partial contradiction with other sub-areas. None of the disciplines can so far provide a satisfactory explanation for how the brain works and accordingly cannot yet give a detailed prescription for the construction of truly "intelligent" systems [45] (see also Chapter 7).

6.4. Emulated brain function

Another possible way of classification can be done according to the brain function that is emulated. This can range from vision, audition, multimodal perception, and motor control over language processing, decision-making, reasoning, and planning, to emotions, learning, and consciousness. In sum, the effort spent so far in truly brain-like approaches to these challenges is still quite limited. The field which has probably received the most attention is computer and machine vision, particularly for the lower processing levels. Interestingly, also in brain sciences, the lower levels of vision are one of the best explored systems of the brain [Nishimoto2011]. In this work, the focus is particularly on the development and implementation of models for multimodal perception, "emotional" situation assessment, and decision-making and their interplay.

6.5. Large-scale brain simulations versus (brain-inspired) cognitive architectures

A methodology related to the bottom-up and top-down categorization of Section 6.2 but perhaps more contemporary for a distinction of brain-inspired approaches is suggested by H. Garis et al. [41] and B. Goertzel et al. [48]. This taxonomy will be described more in detail in the following. The authors distinguish between *large-scale brain simulations* and *(biologically inspired) cognitive architectures*[16]. In the following, a description of these two classes of approaches is given including a number of examples of so far proposed models. For this purpose, the review articles [48] and [41] will serve as the main references. This description does not at this point include a judgment to which extent the individual mentioned models are actually brain-inspired. A critical reflection about the usage of the term "brain-inspired" and the problems coming along with it is given in Chapter 7.

Large-scale brain simulations

Large-scale brain simulations describe systems that attempt to simulate in software the structure and dynamics of particular subsystems of the brain. When looking at existing approaches to large-scale brain simulations, it becomes clear that the scope of interpretation of the notion "brain simulation" is broad. Different researches are approaching this task with very different objectives in mind. H. Garis et al. [41] distinguish between five groups ordering them according to decreasing neurobiological fidelity:

[16] The term "biologically inspired" as used by H. Garis and B. Goertzel mainly refers to architectures inspired by the brain and shall therefore be described under the term brain-inspired cognitive architectures in the following.

1. Models, which can actually be connected to parts of the human brain or body and that can serve the same role as the brain system they emulate. An example is Boahen's artificial retina [16].
2. Precise functional simulations of subsystems of the brain, their internal dynamics, and their mapping of inputs to outputs that explain exactly what the brain sub-system does to control the organism.
3. Models, which quantitatively simulate the generic behavior and internal dynamics of certain brain sub-systems, however, without precisely functionally simulating these sub-systems. The best known examples of this type are Markram's cortical models promoted within the Blue Brain Project [77] and its continuation, the Human Brain Project[17]. Furthermore, such approaches are amongst others targeted by Izhikevich's simulations [56] and Edelman's brain-based devices [62].
4. Models, which quantitatively simulate subsystems of the brain or whole brains at a high level, not including a simulation of the particular details of dynamics or inputs/outputs. Such approaches have the aim to explore some of the overall properties of the given system. Examples are Just's CAPS work [122] or Horwitz's cognitive simulations [54].
5. Models, which demonstrate the capacity of hardware to simulate large neural models. These models are based on particular classes of equations. However, there is no claim about the match of the models with empirical neuroscience data. Examples are Boahen's Neurogrid work [16], Modha's cat brain simulation [7], or S. Furber's SpiNNaker architecture [60].

All of the abovementioned approaches are validly called large-scale brain simulations but constitute very different forms of research of which not all might be suitable for Brain-Like AI design. According to H. Garis, the first two categories are adequate to serve as components of brain-inspired cognitive architectures or other AI systems. Simulations in the third and fourth category are useful for guiding neuroscience or hardware development but are not directly useful for AI. Finally, the fifth category is not directly useful, neither for neuroscience nor AI, but it serves as "proof of principle" with the motivation to lead on to other, more directly useful work in later steps.

H. Garis points out that at present state of technology, large-scale brain simulations have proven to be useful mainly for refining equations used for neural and synaptic modeling and for helping to substantiate conceptual models of brain structures and functions by connecting these models with detailed electrophysiological data in working simulations. They inform us about the dynamics of brain regions and allow us to probe the complexity that underlies structures such as cortical columns and the emergent nonlinear coherence that arises when large numbers of neurons are appropriately coupled. Nevertheless, detailed brain simulations do not yet yield intelligent behaviors not only due to a lack of processing power of (still inadequate) hardware for simulation but more importantly due to a lack of knowledge of the intermediate-scale structure of the brain, so as to be able to encode it into simulations. Furthermore, an embodiment of brain signals seems to be important. However, this aspect has been seldom considered so far in brain simulations.

H. Garis et al. [41] indicate that in case large-scale brain simulation research programs were successful, the biggest benefits are still lying ahead including the followings:

1. Gathering and testing neuroscience data
2. Cracking the neural code
3. Understanding neocortical information processing
4. A novel tool for drug discovery for brain disorders
5. A foundation for whole-brain simulations
6. **A foundation for human-like Artificial General Intelligence**

[17] http://www.humanbrainproject.eu/

Garis at al. [41] point out that it is not yet clear whether large-scale brain simulations will be the first approach to lead to success in human-like intelligence, but it is certainly a plausible and promising approach and different researchers in this field have set their long-term sights specifically in this direction.

(Brain-inspired) cognitive architectures

(Brain-inspired) cognitive architectures attempt to achieve brain-like functionalities by emulating the brain's high-level architecture without necessarily simulating its lower-level specifics [48]. The term *brain-inspired* (or *biologically-inspired*) *cognitive architectures* became common only within the last years through the DARPA funding program administered by the Information Processing Technology Office. Nevertheless, the basic concept of cognitive architectures itself is as old as the field of Artificial Intelligence. While there is no rigid demarcation that separates brain-inspired cognitive architectures from cognitive architectures in general, the term is intended to distinguish cognitive architectures drawing significant direct inspiration from the brain and those based exclusively (or nearly exclusively) on models of the mind [48]. While brain simulations are intended to display not only similar functions to a brain, but also closely similar internal structures and dynamics, brain-inspired cognitive architectures are mainly intended to display (still loosely) similar functions to a brain. They furthermore aim at displaying internal structures that are conceptually inspired by the brain (and not just the mind) but not necessarily extremely similar to it. In practice, drawing a connection between the organization and the activation patterns of the brain and functions of the mind that emerge from them is certainly still a highly challenging task. Thus, the “loosely similar functions to the brain” are in many cases still extremely loose and it is doubtful if these approaches should actually be labeled as “brain-inspired cognitive architectures” or rather simply as “cognitive architectures”. In their survey of cognitive architectures, W. Duch at al. [36, 48] divide existing cognitive architectures into three paradigms:

1. **Symbolic Architectures:** Symbolic paradigms follow a long tradition in AI and are based on the assumption that the mind exists mainly to manipulate symbols that represent aspects of the world or themselves [93]. Examples for symbolic architectures are amongst many others SOAR [66], EPIC [105], ICARUS [69], NARS [145], or SNePS [113]. In [48], they are considered to be psychology-inspired cognitive architectures instead of brain-inspired approaches. While symbolic architectures contain many valuable ideas and have yielded some interesting results, it is doubtful whether they will give rise to the emergent structures and dynamics required for human-like general intelligence.
2. **Emergentist Architectures:** Emergentist cognitive architectures consider abstract symbolic processing to result and emerge from lower-level subsymbolic dynamics, which are in most cases biologically inspired up to a certain extent. They are designed to simulate neural networks or other aspects of human brain function [48]. A few examples for emergentist architectures are HTM [51], DeSTIN [9], IBCA [102], Cortronics [117], or NOMAND [37]. Furthermore, there exists a set of emergentist architectures focused specifically on developmental robotics [74] to control robots without significant „hard-wiring“ of knowledge and capabilities. Here, robots learn via their engagement with the world [48]. Examples for existing architectures are DAV [49], SAIL [148], FLOWERS [11], and IM-CLEVER [81]. Similar to classical AI connectionist systems, emergentist cognitive architectures have proven to be strong in recognizing patterns in high-dimensional data, reinforcement learning, and associative memory. However, probably due to their so far only quite superficial analogy to brain circuits, they have not yet led to the emergence of any brain-like functions [48].
3. **Hybrid Architectures:** Due to the complementary strengths and weaknesses of symbolic and emergentist approaches, researchers have started recently to focus on integrative, hybrid architectures. These combine subsystems operating according to the two different paradigms

described above [48]. Combinations have been suggested in many different ways. Examples are the connection of a large symbolic system with a large subsymbolic system or the creation for populations of small agents, each of which is both symbolic and subsymbolic in nature [48]. Examples for hybrid cognitive architectures are CLARION [120], DUAL [88], LIDA [40], ACT-R [71], MicroPsi [10], Polyscheme [23], 4CAPS [58], Shruti [114], the Novamente AI Engine [43], 4D/RCS [2], or OpenCogPrime [47]. In [89], N. Nilsson claims that *"AI systems that achieve human-level intelligence will involve a combination of symbolic and non-symbolic processing."*

Résumé

In summary, as outlined by B. Goertzel at al. in [47], today, *"brain simulations tell us about cortical columns and about the way collections of neurons "spontaneously" organize into collectives, but they do not yet tell us anything specific about how brains achieve goals, select actions, or process information. On the other hand, (brain-inspired) cognitive architectures tell us how brains may do things, but so far their intelligent behaviors are quite simplistic compared to real brains."* They consider three possible future directions that could lead to the emergence of human-like Artificial Intelligence:

1. Large-scale brain simulations, which simulate multiple brain regions and their interconnections, thus verging on being brain-inspired cognitive architectures.
2. Brain-inspired cognitive architectures, which integrate more detailed neural dynamics into their processing, enabling greater creativity and flexibility of response.
3. Hybrid architectures that link brain-inspired cognitive architectures elements with brain simulation elements.

B. Goertzel at al. give preference to the third option and argue that this will be the most rapid approach towards the twofold goal of understanding the brain and emulating human-like intelligence in computers. In principle, this approach can be considered as an addressing of the problem of emulating the brain by a combined bottom-up neuroscientific and top-down cognitive approach. With this, it is hoped to learn more about the crucial intermediate levels of cognition, about which the least body of knowledge is available currently [45].

7. General challenges and stumbling blocks

Considering the potential benefits of using the brain as an archetype for intelligent system design, it is at first glance surprising that so far only relatively limited attention has been paid to this approach in the field of Artificial Intelligence in comparison to merely mathematically and algorithmically guided concepts. Of course, attempts for the design of Brain-Like AI have existed since the very beginning of AI – with its most popular example being artificial neural networks (see Chapter 5). However, up to now, inspiration from the brain has mainly been drawn just on an abstract level not really justifying the label "brain-like" or "brain-inspired" intelligence [137]. As discussed in the following sub-sections, the reasons for this are multiple. While part of them are purely scientific challenges, others have a more "socio-political" character based on different views, perceptions, and ideologies of different AI researchers. The following points seem obvious once they are as explicitly formulated as it is done in this article. However, in the past, the issues AI researchers chose to investigate led to considerable confusion and misunderstandings, particularly amongst younger researchers having entered the field of AI only once it was already as diverse and heterogeneous in its objectives, methods, and ideologies as it is today. I myself at the beginning of my scientific career can be included into this group. Thus, outlining the challenges to face and the stumbling blocks to overcome can be very valuable for the sake of better clarity and to avoid a repetition of errors that could have been avoided by learning from the past.

7.1. Decipher the complexity of the brain

The most important reason for the quite limited "brain-inspiredness" of existing AI approaches lies most certainly in the complexity of the brain and the difficulty to understand it. Existing models in brain sciences are often still only abstract and descriptive instead of a functional character and contain blank spots and inconsistencies. T. Deutsch [34] describes the problem as follows: *"Various sciences have gathered a vast amount of information on the human mind. An unmanageable flood of different theories, ideas, and approaches derived from psychology, neurology, and philosophy could be used as starting points. The problem is: They are piecemeal – no holistic model is provided."*

What is particularly missing is an understanding of the intermediate levels of cognitions, i.e., how neural correlates can actually result in cognitive functions. B. Goertzel [45] formulates this problem as follows: *"On the one hand, the cognitive sciences provide very clear advice regarding what the overall "conceptual architecture" of an Artificial General Intelligence (AGI) system should be like ... We know what the major regions of the brain do, and we also have a decent working decomposition of human cognition into a list of interacting yet significantly distinct faculties. This high-level architecture can be emulated in AGI systems. On the other hand, the cognitive sciences provide a variety of suggestions regarding specific low-level mechanisms for carrying out intelligent processing, such as perception, learning, and memory. However, the low-level messages from the cognitive sciences are more controversial than the high-level ones for two reasons. First, there is less agreement on them among contemporary experts. And second, it's not always clear that emulating human psychological or neural behavior is a practical approach to implementing intelligence on radically un-brain-like hardware. Cognitive theorists recognize that there is more to the human mind/brain than its high-level architecture and low-level mechanisms. However, the cognitive sciences to date have had relatively little to say about the crucial "intermediate level" of intelligence. This is the main reason that the cognitive sciences don't yet provide really powerful prescriptive guidance to AGI designers. The cognitive sciences tell us what major parts a mind/brain should have, and they describe some low-level mechanisms that can help these parts to carry out their functions, but they say precious little about how the different parts all work together, and how the low-level mechanisms coordinate to give rise to higher-level dynamics."*

M. Looks and B. Goertzel [73] further indicate: *"The best approach to Strong AI at present, we suggest, is to learn what we can from the brain about what sort of high level architecture and general dynamics and representations are useful for achieving general intelligence under conditions of limited computational resources – and then fill in the algorithmic level with representations and algorithms that make sense in terms of the mathematics, computer science, and computer hardware and software that we know. This attitude leads into an integrative approach to AI, in which one takes a general architecture loosely inspired by human cognition, and then uses it to bind together components drawn from various areas of mathematics and computer science."* The suggestion to fill blank spots with algorithmic solutions is without doubt reasonable and valid to achieve functioning systems. However, this approach has to be followed with caution as it has in practice led to further problems (see Section 7.5 for further details). In summary, researchers that aim at emulating brain functions for technical purposes need, apart from sophisticated skills in engineering, a relatively profound understanding of the state of the art knowledge in brain sciences. Apart from this, they need the analytic capacity to detect inconsistencies and blank spots in brain theories and the ingenuity and creativity to propose solutions how to resolve them.

7.2. Find the right level of abstraction and detail

A second point crucial to successful brain modeling is the specification of the right level of abstraction and detail from which to start. This decision certainly depends on the specific requirements of the system in mind (e.g., what processes need to be explained by the developed model). Starting with a neuroscientifically inspired bottom-up design (as in large-scale brain simulations) on a level with too much detail – e.g., with the modeling of molecular processes in single neurons when trying to understand the general information flow in larger cortex structures – bears the danger of becoming lost in unnecessary details not directly relevant for the given problem. Similarly, starting with a top-down design (as generally in cognitive architectures) and remaining with brain analogies on a too high level of abstraction can lead to models that are too loosely patterned in regards to the organization and principles of the brain. Such designs tend to contain rather simplistic metaphors instead of sound models of the brain/mind. In such approaches, researchers are in danger of falling back to classical AI methods and developing solutions of mere mathematical and algorithmic character. In this context, O. Sporn [118] comments that *"it will be futile and scientifically meaningless to attempt to build intelligent systems by slavishly imitating or replicating the real brain. On the other hand, the extreme computational functionalism of the classical AI movement has done little to advance flexibility and robustness in intelligent systems. What is needed is a new synthesis of brain, cognitive and engineering sciences to harness the complexity of biological systems for the design of a new generation of more capable brain-like intelligence."* Similarly, in his article about *Neuroscience and AGI*, R. Koene [61] points out that *"a recurring argument against borrowing from neuroscience in the development of AGI has been to note that the low-level design of the brain is very complex, possibly needlessly complex for general intelligence. But other difficulties arise when one instead chooses the most obvious alternative approach: Observing high-level processes and implement those"*. He raises his concerns about the strong reliance on vastly simplified models of cognition in AGI: *"The aspects of cognition that are well-explained by the popular cognitive architectures cited in AGI research are based, in part, on cherry-picked experiments and corresponding data about human cognitive processes that are the easiest ones to characterize."*

7.3. Overcome the lack of interdisciplinarity and collaboration

A further possible reason for the limited progress in Brain-Like AI so far can be found in the fact that many AI researchers – who are still mainly computer scientists and engineers – naturally lack deeper understanding of established brain theories. Obtaining this knowledge, e.g., by regular and tight cooperation with brain researchers, could in the future make a huge difference. However, setting up fruitful interdisciplinary collaborations which would benefit from synergies still requires considerable effort. In his article *What Can AI Get from Neuroscience*, S. Potter [99] states: *"Yet, little attention in the AI field has been directed toward actual brains. Although many of the brain's operating principles are still mysterious, thousands of neuroscientists are working hard to figure them out. Unfortunately, the way neuroscientists conduct their research is often very reductionistic, building understanding from the bottom up by small increments. A consequence of this fact is that trying to learn, or even keep up with, neuroscience is like trying to drink from a fire hose. General principles that could be applied to AI are hard to find within the overwhelming neuroscience literature. AI researchers, young and old, might do well to become at least somewhat bilingual."* He further suggests: *"It's time for AI to move in the brainwards direction. This could involve PhD programs that merge AI and neuroscience, journals that seek to unite the two fields, and more conferences at which AI researchers and neuroscientists engage in productive dialogs. Neuroscientists have not exactly embraced AI either. Both sides need to venture across the divide and learn what the other has to offer."* Similarly, B. Sendhoff et al. [111] point out: *"New principles are usually found at the interfaces between existing disciplines, and traditional boundaries between disciplines have to be broken down to see how complex systems become simple and how the puzzle can be assembled. Each of us is rooted in a certain community which we have to serve with the results of our research. Looking beyond our fields and working at the interfaces between established areas of research requires effort and an active process. It is our belief that we have to more intensively pursue research approaches that aim at a holistic and embedded view of intelligence from many different disciplines and viewpoints."*

A further fact that contributes to the problem is that researchers who are actually active in the field of Brain-Like Artificial Intelligence are currently still located on the borders of other disciplines. So far, they have spent only moderate effort on collaborating amongst each other. To catalyze the emergence of the field of Brain-Like AI, it will be necessary that they start to join forces.

7.4. Avoid a misapplication of terms

The domain of Brain-Like Artificial Intelligence is still relatively new and dynamic and only beginning to establish. It is up to now no homogenous research field with well-defined borders and it must struggle with many difficulties and barriers in addition to the ambitious challenge of understanding and emulating the brain based upon incomplete knowledge from neuroscience, cognitive sciences, and other disciplines.

One problem with this field that has led to considerable confusion not only amongst the general public but also amongst AI researchers themselves is that there do not exist guidelines or rules for when a model may be called "brain-like" or "brain-inspired". There are no broadly accepted definitions that define the attribute "brain-like" and how the attribute can be implemented and tested [53]. B. Sendhoff et al. [111] state: *"What is Brain-Like Intelligence? Although it seems necessary to have a good understanding of what one wants to create before one starts, there is no crisp and clear definition."* Unfortunately, the term "brain-like" is therefore sometimes misapplied or misused either knowingly or unknowingly. Knowingly, this happens for marketing purposes – as the label brain-like (or similar) is often (partly unconsciously) perceived as a synonym for highly sophisticated and advanced hardware and software technology amongst the general public. On the other hand, in the past, this has also occurred partly unknowingly due to engineers' and computer scientists' limited understanding of the difference between the structure and information processing principles of the brain and commonly used computer architectures and programs.

In both cases, this has sometimes led to a mere transfer of terms from brain sciences to AI rather than a transfer of sophisticated concepts and principles. T. Deutsch [34] advises caution in this context: *"One has to be careful when using terms from human sciences. They tend to end as a label for something, which has nothing to do with the original concept they described"*. Several textbooks, articles, and PhD theses written in the past have shown that a conclusive and tight merging of biological and technical concepts is not that straightforward. There exists literature that starts with a description of biological, neural, and cognitive principles in the first chapters and finishes with technical solutions in the last ones without a direct, notable correlation and connection between the former and the latter [5]. In other approaches that claim to be brain-inspired, some correlations between certain mechanisms in the brain and the developed models can be deduced. However, what is still often missing is a clear statement about which parts of the models have taken inspiration from the brain and which elements were guided by mathematic-algorithmic methods and engineering considerations only [100, 107, 121].

7.5. Prevent a drive against the traffic

While Brain-Like AI generally aims at implementing concepts from the brain for the design of technical systems, there exists on the other hand a research niche where engineers aim at understanding the brain by studying the structure and behavior of common (not brain-inspired) computational systems and programs [8]. Although such approaches can in certain cases bring some new interesting insights [111], in practice this has on occasion been counterproductive in the past as it has misguided researchers who did not have a clear picture of the differences between today's computational machines and the brain [137]. It should be noted that – if these computational systems and programs were not designed by taking inspiration from nature and the brain/mind – it is scientifically "dubious" to draw conclusions about the functioning of the brain from these designs, at least, without further consultation with brain scientists and their theories about brain function. L. Miller states that AI researchers have to be criticized for this in particular as this has not produced theories whose adequacy can be tested by empirical research [82]. M. Looks and B. Goertzel [73] formulate this criticism in a more moderate way: *"We are neutral as to how directly the brain's* *neuronal network structure and dynamics relate to its cognitive representations and algorithms, and also as to how closely the brain's knowledge representation resembles formal logic and how closely its dynamics resemble logical inference. These are very important questions, but neuroscience has not yet progressed far enough to give us the answers. No one knows how an abstract proposition like "Every boy has a dog that every girl likes to call by a special name" is represented or manipulated or learned through experience in the human brain, and until we know this, we won't know the extent to which the conceptual premises of the most popular neural net or logic based approaches to AI are correct."*

To be fair, it has to be mentioned that there has started to evolve a research niche called *AI-Inspired Biology* [24] where cognitive scientists and biologists have joined forces with AI researchers with the aim to illustrate ways in which AI can influence research on natural cognition and formulate new research questions in biology and brain sciences. Treating such topics in an interdisciplinary team instead of just amongst engineers certainly has higher probabilities of success.

7.6. Tolerate and respect differences in scientific ideology

Artificial Intelligence is not a homogeneous research domain but actually deeply divided into sub-fields with different ideologies, methodologies, and targets. It requires a profound understanding and knowledge about the history and developments in AI to gain an awareness (and maybe also tolerance) of the differences in approaches and aims of the distinct sub-disciplines. This fact is particularly problematic in the field of Brain-Inspired AI. While other AI domains are focused on approaches based on mathematic, algorithmic, and computation theories, Brain-Like AI aims (or at least should aim) at using the (human) brain as archetype. It therefore has different objectives and methodologies and targets an absolutely different level of complexity than the mathematic-algorithmic approaches of the more "classical" AI. The problematic of the differences in objectives, ideology, and methodology of different AI domains comes into play when a researcher of one sub-field evaluates the work of a researcher of the other sub-domain. In practice, it seems to happen rather frequently that editors and funding agencies assign research articles or scientific research proposals to reviewers with an "opposing ideology" about how research in AI should be done. In certain cases, this can lead to a misinterpretation and at times an unjustified rejection of scientific work of related but opposing disciplines. This phenomenon is not particularly new in AI (and is probably also common in other fields of science). Furthermore, like today, already in 1960, the competition for research funding in AI was intense. As pointed out in [70], there have thus always been personal animosities between AI researchers of different groups. In 1969, for instance, M. Minsky and S. Papert published their famous work on *Perceptrons* [84] criticizing computational models of the nervous system, which showed *"with unanswerable mathematical arguments that such models were incapable of doing certain important computations"* [70]. This killed most research in neural computing for the following 15 years. Much later, S. Paper admitted in an interview [70]: *"Yes, there was some hostility behind the research reported in Perceptrons ... part of the drive came from the fact that funding and research energy was dissipated ... money was at stake."* In recent times, these conditions have turned out to be particularly hard for scientists working in Brain-Inspired AI. As they are still a minority compared to other AI research communities, the statistical probability that their work is judged (and sometimes misjudged) by experts of opposing fields is relatively high. Of course, misjudgment of scientific quality of work does not only occur in a one way direction from classical AI to Brain-Like AI but also the other way around. A. Sloman [111] points out that *"lessons learned from and within classical Artificial Intelligence remain relevant to the research program of creating brain-like intelligence and the reaction against everything related to classical AI may even have held up progress."* However, as the field of Brain-like Artificial Intelligent is still very novel and dynamic and can so far only count on a small community of researchers compared to traditional AI, it is in this case still a quite unequal fight, which can drastically slow down necessary progress.

7.7. Establish suitable measures for validating progress and success

As in any other field of engineering and science also in Brain-Like Artificial Intelligence, the validation of progress and success is a crucial element [112]. In Brain-Like AI, the aims, methodologies, and the level of complexity of problems are different from other fields of AI. Accordingly, different evaluation mechanisms for judging the value and success of developed approaches have to be found.

Applied AI tries to achieve some kind of computational behavior that can solve mainly circumscribed and limited problems that would need cognitive capabilities when done by humans. Brain-Like AI aims at using similar organizational structures and information processing principles like the brain to achieve such tasks. For example, it is impossible to isolate the "person-recognition-brain-circuits" from the "fruit-recognition-circuits" or the circuits for planning a travel route from the ones taking a decision about what to eat for breakfast. Thus, Brain-Inspired AI cannot focus on isolated problems. It has to aim at solutions targeting human cognitive capabilities at a more general and global level. It has to target topics such as human perception, situation assessment, or human decision-making in a more holistic way and cannot just focus on singular topics such as "face recognition" or "path planning" in a specific context.

In Applied AI as it focuses on very specific and circumscribed problems, an evaluation and comparison of results amongst each other is relatively straightforward. For example, for a particular classification problem, the number of true and false positives can be determined and compared in different approaches. A qualitative comparison of machine performance with human performance is generally out of the scope of the evaluation.

In contrast, in research fields like Brain-Like AI and also Artificial General Intelligence (AGI), things are not that straightforward. In AGI (before Strong AI), which has been around since the beginning of AI, the challenge of effectively evaluating performance has been troublesome for scientists for decades. Strong AI has the aim of achieving a general level of intelligence instead of just measuring the performance of an approach in very specific sub-tasks. A. Adam [1] comments that *"if the aim of AI is primarily to create an artificial mind, then the success or failure of the whole AI project should be judged against this one goal"*. S. Legg [72], who provides an extensive overview and discussion of suggested methods for measuring biological and artificial intelligence, points out that the first fundamental problem for judging artificial intelligence is that *"nobody really knows what intelligence is"*. R. Davis [30] claims that the basic question is not just "What is intelligence?" but equally important also "Why is intelligence?" R. Sternberg et al. [119] point out that *"viewed narrowly, there seem to be almost as many definitions of intelligence as there were experts asked to define it"*. This problem is certainly "*especially acute when we need to consider artificial systems"* – e.g., the computer – *"which are significantly different to humans"* [72]. In the past, the most prominent approach for evaluating „intelligence" in the field of AGI (before Strong AI) was the Turing test, originally suggested by A. Turing in 1950 [123]. According to the Turing test, a machine is "intelligent" if a human judge cannot distinguish its answers from the answers of a person in a communication without direct physical contact. However, in later years, the Turing test has been heavily criticized [147] and has been subject to further changes and extensions, e.g., the total Turing test [106] which also incorporates video signals and the possibility to pass physical objects "through the hatch" to allow the interrogator to evaluate the subject's perceptual abilities and its "manipulative" abilities. This has led to an extension of earlier efforts using computer vision and robotic object manipulation. However, passing such extended Turing tests can just be – if at all – a necessary but not a sufficient condition for intelligence [85]. The Turing test is based upon the (doubtful) assumption that *"once having a sufficiently precise theory of the mind, it becomes possible to express this theory in a computer program. If the program's input-output behavior matches corresponding human behavior, this is evidence that some of the program's mechanisms could also be operating in humans"* [106]. One major problem with the whole Turing test is that it can just check for an indistinguishability of human behavior and the „behavior" a program emits in a particular situation. However, it is important to note that just because two things are indistinguishable from a certain perspective, they do not at all have to be the same. Judging progress and success in AGI thus remains a hotly debated issue.

Similar to AGI, finding adequate evaluation mechanisms in Brain-Like AI is a puzzling task. Like in AGI, the objectives in Brain-Like AI are much more complex than in Applied AI. Therefore, it is much more difficult to achieve quantitatively comparable results in the short term. After all, in Brain-Like AI – if done properly and without too many "workarounds" – the overall functionality of a model only starts to emerge when the whole system starts to sufficiently resemble the organizational structures and information processing principles of the brain. Furthermore, a detailed comparison of the performance of developed brain-like models with methods used in Applied AI or other fields of engineering – as frequently requested from reviewers – is often simply not feasible due to the fact that the problems addressed with brain-like models often simply do not match in terms of complexity with problems addressed in Applied AI and related domains for the following reasons:

- **Unequal Performance Comparisons:** The aim of Brain-Like AI is usually to provide more general, "global" solutions and not only task-specific solutions as normally addressed in Applied AI. A brain-like model targets for instance the problem of (machine) perception in general [138] and not just the distinction of ten specific faces in a number of video frames or single images. Thus, research efforts spent until reaching a more global solution – which also needs cooperation with brain-sciences on unresolved questions of brain functioning – are certainly much higher. Quantitatively comparing this "general purpose" solution to a "single purpose" approach that is highly specialized and optimized to one single task is certainly not a fair competition if the evaluation concerns only the task for which the "special purpose system" has been optimized.
- **Lack of Systems to which to Compare:** Brain-Like Artificial Intelligence targets particularly challenges and applications for which today there are still no satisfactory solutions provided by current technical approaches. In order to compare a particular brain-inspired approach with other purely mathematically/algorithmically-based technical approaches for such a "complex" application, it would therefore be necessary to do both:
  1. Develop the brain-inspired approach;
  2. Develop, adapt, and customize purely technical approaches for the given non-trivial problem – developments that can, if done properly, themselves easily take several years or even decades for each chosen approach;

  This would however need an enormous effort that could only be achieved by combined major resource and time investments from various research groups with different backgrounds having a common interest in amicable competition. Applying for funding for such an undertaking seems to be however outside the current funding frameworks.
- **Different Requirements for Comparison from Different Disciplines:** Brain-Like AI faces an additional difficulty in comparison to other sub-disciplines of AI and engineering as it is very interdisciplinary. B Sendhoff et al. [112] point out: *"We are not clear yet, whether we shall position ourselves more within the scope of* brain *science or technology. In the first case, success has to be judged by neurophysiological or psychological experimental data as is the case in computational neuroscience. In the second case, the target is to provide evidence that the realized system accomplishes its intended requirements. Of course, in this case we have the initial burden to clearly define what the intended requirements are against which we want to judge our progress. The fact that there is a continuous transition between both extreme stand-points makes the measurement process even more ambiguous."*

Seeing the difficulties of quantitative comparisons of Brain-Like AI approaches to other conventional existing technical approaches and considering the fact that we are at the very beginning of the development of the field of Brain-Like AI make it necessary to reach for validation methods that are different from the ones common in more classical fields of engineering and Applied AI. As outlined above for the field of AGI which faces partially similar challenges, the discussion of how to do this is still ongoing. Nevertheless, the fact that in Brain-Like AI we can judge both "brain similarity" and "system accomplishment" – as indicated in point three of the itemization above – can actually be considered as an advantage concerning validation criteria in comparison to AGI. While AGI usually still has to rely on external observations of emitted „intelligent behavior" only (e.g., the Turing test), which has proven to be problematic, Brain-Like AI can additionally count on an analysis of internal similarities of developed models with the brain on a neural/cognitive level. Together with the emitted function of the implemented technical system, the analogies in organizational structures and information processing principles of the underlying model can be compared to the ones of the brain to obtain a judgment of its quality. It is important to note that an ideal brain-like model should show both similarities in externally emitted function and in internal organization and processing! Such an evaluation becomes particularly interesting if learning mechanisms are integrated into a model. If these learning mechanisms were actually sufficiently „brain-like", similar structuring and function principles should evolve after this learning as they can be observed in the developed (human) brain. In the long run, such "self-developed" similarities could be an ultimate proof for adequate brain-like design.

8. Recommendations for a way to go in future

As outlined in the last section, the field of Brain-Inspired Artificial Intelligence is not completely non-problematic for different reasons. While part of the difficulties are issues of "science-policy" and could therefore be addressed by broadening researchers' still sometimes a bit too one-sided view on the topic via a promotion of interaction between disciplines, the most severe drawback is still the fact that the brain is presently not sufficiently understood on all levels to technically emulate its complete function based on existing neuro-cognitive models alone. In the future, symbiotic developments of AI researchers together with brain scientists might be able to change this fact. However, this process will require time. B. Goertzel [45] describes this problem and suggests a possible way out of this dilemma as follows: *"Given the current state of the cognitive sciences, the present-day Artificial General Intelligence (AGI) designer has several recourses:*

- *Firstly, he can simply wait until the cognitive sciences advance further, and give more thorough prescriptions for AGI design.*
- *Secondly, he can ignore the cognitive sciences and attempt to design an AGI on other grounds – e.g. based on the mathematics of reasoning, or based on general considerations regarding the dynamics of complex self-organizing systems. Of course it's worth reflecting that many of these „other grounds" – such as mathematical logic – were originally conceived as qualitative models of human thought. But still, in spite of this historical fact and the strong intuitive feelings associated with it, the empirical cognitive sciences have not yet substantiated any deep connections between mathematical logic and human cognition.*
- *Or, thirdly, he can seek to create an AGI design that is consistent with the information provided by the cognitive sciences, but also introduces additional ideas filling in the gaps they leave."*

According to the understanding of Brain-Like Artificial Intelligence as followed here, the third suggested approach seems to be the most sensible one for the moment and is therefore the one advocated in this article. However, to avoid confusion, it should always be transparent which parts of the model are actually brain-inspired and which are those that are based on such „technical workarounds". Accordingly, my recommendation for a procedure to follow in the future for the development of Brain-Like AI systems is the following:

1. Use knowledge about the organizational structures and information processing principles of the brain as basis for model and system development as far as available.
2. Based on this, advance the knowledge in brain sciences by reporting detected inconsistencies and blank spots in existing brain theories.
3. In case the emulation of the brain is not possible at a certain point due to blank spots, supplementary logical engineering considerations are allowed to create a functioning technical system. However, it must always be pointed out clearly what "workarounds" have been used and at which place. In fact, such workarounds can in certain cases even enhance the knowledge about the brain by bringing up new hypotheses which have been missing in the big picture about the functioning of the brain. Nevertheless, one always has to be clearly aware of the balancing act of drawing conclusions from such technical solutions back to the brain. In the past, they have far too often led to inappropriate claims about the structure and functions of the brain.
4. Validate the model in terms of both achieved functionalities and similarities to internal structural organization and processing principles of the brain.
5. When having proposed a new potentially relevant hypothesis concerning particular brain functions, aim at bringing this hypothesis to the attention of the respective discipline of brain science (e.g., via peer-reviewed journal publications) with the encouragement to experimentally verify it with empirical brain science data.

During the process of increasing the synergies between Artificial Intelligence and brain sciences in the way proposed above, a bootstrapping process is likely to occur. Brain research will provide better models that can serve as basis for more advanced AI systems. More sophisticated AI systems will give brain scientists the tools to make further discoveries and interpret them [99].

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Discrete Wavelet Transform Method: A New Optimized Robust Digital Image Watermarking Scheme

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Abstract

In this paper, a wavelet-based logo watermarking scheme is presented. The logo watermark is embedded into all sub-blocks of the LLn sub-band of the transformed host image, using quantization technique. Extracted logos from all sub-blocks are mixed to make the extracted watermark from distorted watermarked image. Knowing the quantization step-size, dimensions of logo and the level of wavelet transform, the watermark is extracted, without any need to have access to the original image. Robustness of the proposed algorithm was tested against the following attacks: JPEG2000 and old JPEG compression, adding salt and pepper noise, median filtering, rotating, cropping and scaling. The promising experimental results are reported and discussed.

Keywords: Wavelet transform, watermarking, quantization technique,

1. Introduction

Nowadays protecting the copyright of the digital media has become an important topic due to digital media can be copied and modified easily. Many watermarking techniques have been proposed to solve the copyright protection problem for multimedia images.

The spatial and transform domains are two common methods for image watermarking. Embedding the watermark into the transform-domain generally helps to increase the imperceptibility, security, and robustness. Therefore, at present, most of image watermarking methods are in the transform domain, where DFT [1], DCT [2], DWT [3] are three main transform methods used. In terms of the extracting scheme, watermarking algorithms are also divided into two groups: blind and non-blind watermarking. In a non-blind watermarking the original image is necessary for the watermark extraction whereas in a blind watermarking the original image is not needed for watermark extraction.

The paper is organized as follows: section 2 explains the proposed algorithms for watermark embedding and extraction. Experimental results are presented in section 3.

2. Proposed Watermarking Scheme

Nowadays, most watermarking algorithms use wavelet and quantization techniques; The use of wavelet domain watermarking has the advantage of making the watermark robust against many of the distortions that change high frequency components of image such as compression and low-pass filtering; however, it cannot resist the attacks such as cropping that destroy a whole region of the watermarked image because each pixel of watermark is usually embedded only in one region of the host image.

Most of the wavelet based watermarking methods divide a wavelet sub-band to small sub-blocks and then embed each bit of logo watermark in one sub-block by quantizing the coefficients of that sub-band but for increasing robustness of our scheme against cropping attack, we proposed a method that embeds one logo in each sub-block.

Therefore, each bit of the logo watermark is stored in one coefficient of a sub-block to keep the capacity of watermarking fixed.

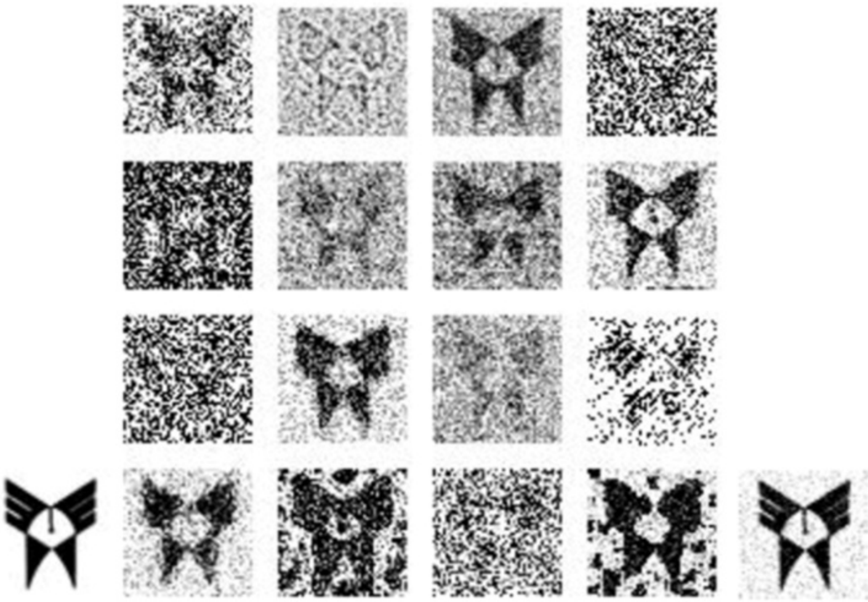
When a region of the watermarked image is destroyed; the whole watermark can be extracted using other regions of the watermarked image by merging extracted watermarks. Figure 1 shows result of merging logo watermarks that were extracted from a compressed (with JPEG2000 algorithm) watermarked image.

2.1. Watermark Embedding Algorithm

Suppose the host image I is a gray-level image with N by N pixels and logo watermark W is a binary image with M by M pixels.

$$I = \{I(i,j) | 1 \le i \le N, 1 \le j \le N, 0 \le I(i,j) \le 255\}$$
$$W = \{W(i,j) | 1 \le i \le M, 1 \le j \le M, W(i,j) \in \{1,0\}\}$$

The watermark is embedded through the following steps:



a b c

Figure 1. (a) Original watermark (b) extracted watermarks after compression(c) merged watermark

Step 1: The host image is decomposed into n level using discrete wavelet transform. We select LL_n sub-band of the decomposed image for watermark embedding.

Step 2: The selected sub-band is divided into small sub-blocks B_k with the size of M×M.

Figure 2 shows the sub-blocks.

Step 3: The logo watermark is inserted to all of the sub-blocks by quantizing the coefficients of them according to the following formula:

$$qk^{'}(i,j) = \begin{cases} mQ \quad , & mQ < qk(i,j) \le (m+0.5)Q \\ (m+1)Q, & (m+0.5)Q < qk(i,j) \le (m+1)Q \end{cases} \quad W(i,j) = 1$$

$$qk^{'}(i,j) = (m+0.5)Q \qquad W(i,j) = 0$$

Where $q_k(i,j)$ is used to represent wavelet coefficients of B_k sub-block and $q_k'(i,j)$ is used to represent the same coefficients after quantization. $W(i,j)$ is the logo watermark, m is an integer and Q is the quantization step size.

Step 4: Finally, with new coefficient values, the host image is reconstructed to form the watermarked image.

The choice of *n* should be made based on an optimal compromise among robustness, invisibility and the attack. With a good choice, the watermark could be made more robust against image degrading. Selecting small *n* can cause to reduce robustness of algorithm but will increase execution speed and decrease the degradation of watermarked image. Selecting a large n can also cause to increase robustness of algorithm but will decrease the dimensions of LL_n region so it causes to decrease number of sub-blocks*(K).*

It is obvious that there is a relation between *N, M, n* and *K,* in optimal case: $N=M\times K\times 2^n$.

2.2. Watermark Extraction Algorithm

Whereas most of methods for watermark extraction require the original image, the proposed method does not. For extracting watermark logo, the size of host image, size of watermark image, quantization step size (Q), level of decomposition (n), number of sub-blocks (K) are needed.

The watermark is extracted through the following steps:

Step 1: The watermarked image is decomposed into level *n* using discrete wavelet transform. LL_n sub-band of the decomposed image is divided into sub-blocks B_k with the size of $M\times M$.

Step 2: Pixels of logo watermark W_k corresponded to each sub-block B_k are extracted with the following formula.

$$W_k(i,j)=\begin{cases}1 & (m-0.25)Q \le q_k(i,j) \le (m+0.25)Q \\ 0 & (m+0.25)Q \le q_k(i,j) \le (m+0.75)Q\end{cases}$$

Where $q_k(i,j)$ is used to represent wavelet coefficients of sub-block B_k, m is an integer and Q is the quantization step size.

Step 3: If no distortion happens for watermarked image, all extracted logos W_k should be the same as the embedded logo.

But if any distortion was happened for watermarked image, the extracted watermarks will be merged by voting to obtain the final result. Merging is done based on the following formulas [4]:

$$W(i,j)=\begin{cases}1 & E(i,j)\ge \frac{1}{2}k \\ 0 & E(i,j)< \frac{1}{2}k\end{cases}$$

$$E(i,j)=\sum_{k=1}^{nK} W_k(i,j)$$

Where $W_k(i,j)$ is used to represent extracted watermark from sub-block B_k and $W(i,j)$ is used to represent the merged watermark. *K* is number of sub-blocks.

3. Experimental Results

In the following experiments, two gray-level images with size of 512 by 512, “Baby” and “Hookah” are the test images. The binary image “IAU” with size of 32 by 32 is used in our simulations as a watermark. Figure 3 shows the watermark. In the experiments Haar wavelet filter was used for discrete wavelet transform. The level of wavelet decomposition (n) and the number of sub-blocks (K) were also assumed to be 2 and 16 respectively.

The proposed watermarking algorithm is evaluated from the point view of embedded watermark transparency and robustness; the result of each is shown in next two sections.

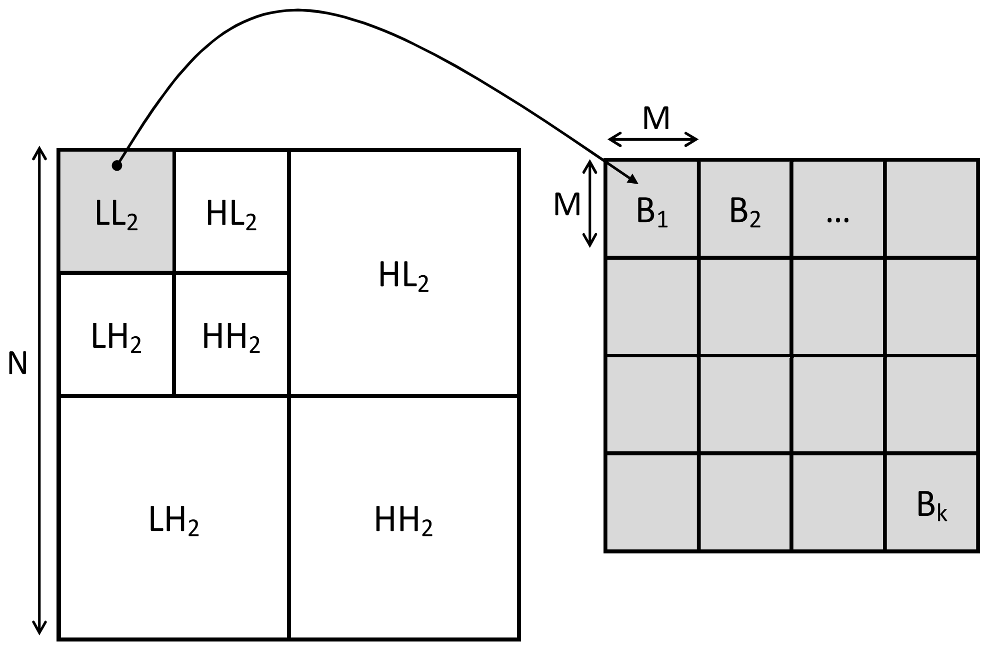


Figure 2. LL_2 sub-band is divided into sub-block

3.1. Image Quality

The PSNR (Peak Signal to Noise Ratio) is widely used to measure the difference between two images based on pixel differences. In the watermarking case, is used to evaluate the quality of the watermarked image. For a $N1\times N2$ pixels image with pixels luminance values ranging from zero (black) to L_{max} white, the PSNR is defined as[5]:

$$PSNR = 10log_{10}\frac{L_{max}\times L_{min}}{MSE}$$

Where MSE is mean square error defined as:

$$MSE = \frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}[I_0(i,j) - I_w(i,j)]^2}{N_1 \times N_2}$$

Where I_o and I_w are the respective luminance values of the original and watermarked images. Selecting a good Q for this scheme is very important because increasing Q can cause degradation of visual perception of watermarked image but increases it's robustness against many attacks; therefore Q and PSNR are in inverse proportion.

But this measure is not very accurate and we can't select the correct Q value according to the PSNR value; the threshold of Q for degradation of watermarked image is different for every image and depends on its spatial frequency. Figure 4 shows original and watermarked images of "Hookah" and "Baby".

Figure 2. The watermark used for embedding

3.2. Robustness Against Image Processing

A set of distortions is applied to the watermarked image and the watermark is extracted from the distorted image. We used bit correct rate (BCR) to evaluate our proposed algorithm and it is calculated from the following equation [6]:

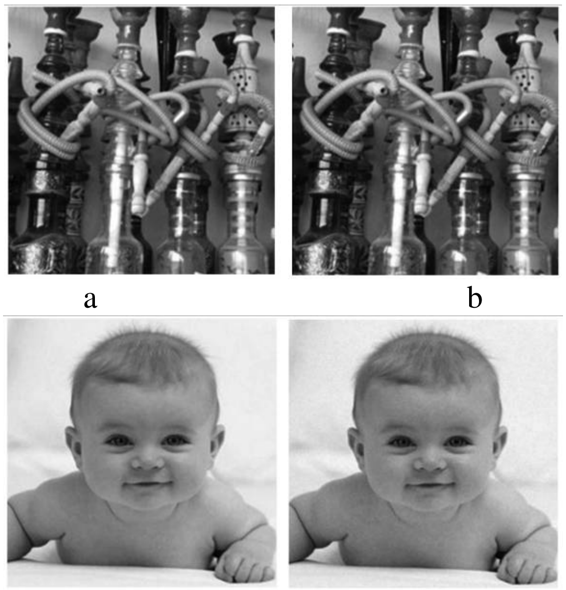


Figure 4. (a) The original “Hookah” image (b) Watermarked “Hookah” with Q=35 (c) The original “Baby” image (d) Watermarked “Baby” with Q=35

$$BCR = \frac{\sum_{i=1}^{M_1} \sum_{j=1}^{M_2} \overline{W(i,j) \oplus W'(i,j)}}{M_1 \times M_2}$$

Where $W(i,j)$ and $W'(i, j)$ are respectively original and extracted watermarks with size of $M1 \times M2$ pixels. The robustness of the proposed watermarking scheme is evaluated against several attacks including adding Salt & Pepper noise, rotation, scaling, cropping, filtering, JPEG and JPEG2000 compression. Table 1 shows PSNR and BCR values of the watermarked images under the above distortions.

Table 1. PSNR (dB) of distorted watermarked images and BCR values of extracted watermarks under different distortions

Host Image	**Hookah** (Q=35)		**Baby** (Q=35)	
Attacks	PSNR	BCR	PSNR	BCR
Jpeg2000 (rate = 0.1 bpp)	36.03	0.99	37.96	0.99
Jpeg (Quality=20%)	32.30	0.91	32.43	0.93
Median Filter (window 7×7)	30.12	0.91	26.76	0.95
Salt & Pepper Noise(nd=0.05)	18.41	0.93	17.85	0.82
Image Resize (scale = ¼)	27.84	0.98	26.14	0.97
Image Rotation (deg = 0.5°)	23.31	0.86	22.23	0.91
Center Crop (40%)	9.33	0.98	7.19	0.98
Surrounding Crop (45%)	9.29	0.95	5.97	0.97

In general digital images are stored and transmitted after image compression. JPEG is more popular among image compression methods than still images. The watermarked images are compressed by JPEG2000 and JPEG compression with different compression ratios. Figure 5(a1) and (a2) show the compressed version of figure 4(a) respectively under JPEG2000 (0.1 bpp) and

JPEG (Quality=20%) compression. The corresponding extracted results are showed in figure 5 (b1) and (b2) with high BCR values (0.99) and (0.91).

We investigated the robustness by smoothing the watermarked image with median filter whose window size is 7×7 pixels. Figure 5(a3) shows the smoothed version of figure 4(a) under median filtering. The corresponding extracted result is shown in figure 5(b3) with high BCR value (0.91).

We evaluated the robustness by adding Salt & Pepper noise to the watermarked image. In this test, the density of additive noise was 0.05. Figure 5(a4) shows image of figure 4(a) after adding Salt & Pepper. Extracted watermark is showed in figure 5(b4) with high BCR value (0.93).

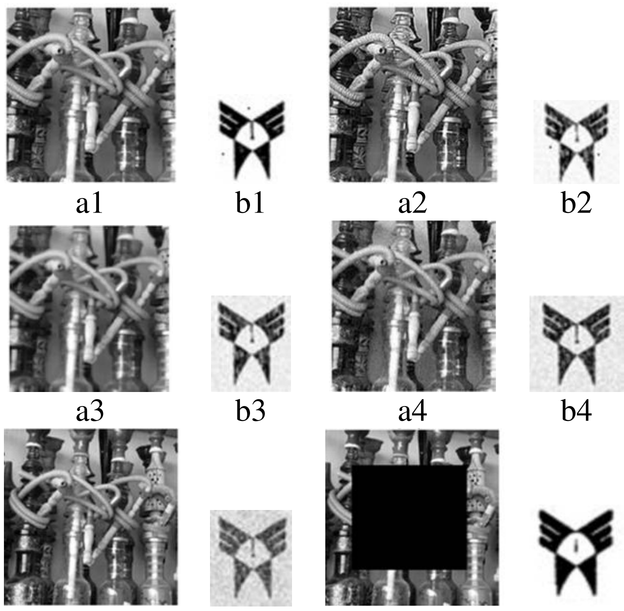
In figure 5(a5), even though the wavelet transform is not rotationally invariant, our proposed method can extract the watermark for small rotations. Extracted logo from 0.5° rotated watermarked image with BCR value of (0.86) is shown in figure 5(b5).

As we predicted, this watermarking method is very robust against image cropping. We extract 98% and 95% of watermark from the watermarked images that was cropped from center and surrounding with ratios of 40% and 45% respectively. Figure 5(a6) and (a7) show these cropped watermarked images and their corresponding extracted results are showed in figure 5(b6) and (b7). Image resizing is also a common geometric transformation. The watermarked image is reduced to 25% of its original image size. Next, in order to detect the watermark, the reduced image is recovered to its original dimensions. Figure 5(a8) shows the reduced and recovered version of Figure 4(a) and extracted watermark with high BCR value of (0.98) is shown in figure 5(b8).

The above simulations and analyses have all confirmed that the proposed scheme has high robustness against common geometric transformations, filtering, and compression. However, this scheme cannot well resist rotation and additive noise attacks. In some cases, we cannot detect the watermark correctly.

4. Conclusions

This paper has described a scheme for digital watermarking of still images based on discrete wavelet transform. In the proposed method, the embedded logo watermark can be extracted without access to the original image. It has been confirmed that the proposed watermarking method is able to extract the embedded logo watermark from the watermarked images that have degraded through compression, filtering, cropping and scaling. Although this algorithm is not robust against rotation, it can completely extract the watermark from watermarked images that lose about 35% of their areas by cropping attack.



a7 b7 a8 b8

Figure 6. (a1), (a2), (a3), (a4), (a5), (a6), (a7) and (a8) watermarked image is degraded respectively through JPEG2000 compression, JPEG compression, median filtering, adding Salt&Pepper noise, rotating, center cropping, surrounding cropping and scaling. (b1), (b2), (b3), (b4), (b5), (b6), (b7) and (b8) The corresponding extracted watermarks.

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Hybridization of Fuzzy Clustering and Hierarchical Method for Link Discovery

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Abstract

Clustering is an active research topic in data mining and different methods have been proposed in the literature. Most of these methods are based on numerical attributes. Recently, there have been several proposals to develop clustering methods that support mixed attributes. There are three basic groups of clustering methods: partitional methods, hierarchical methods and density-based methods. This paper proposes a hybrid clustering algorithm that combines the advantages of hierarchical clustering and fuzzy clustering techniques and considers mixed attributes. The proposed algorithms improve the fuzzy algorithm by making it less dependent on the initial parameters such as randomly chosen initial cluster centers, and it can determine the number of clusters based on the complexity of cluster structure. Our approach is organized in two phases: first, the division of data in two clusters; then the determination of the worst cluster and splitting. The number of clusters is unknown, but our algorithms can find this parameter based on the complexity of cluster structure. We demonstrate the effectiveness of the clustering approach by evaluating datasets of linked data. We applied the proposed algorithms on three different datasets. Experimental results the proposed algorithm is suitable for link discovery between datasets of linked data. Clustering can decrease the number of comparisons before link discovery.

Keywords: Hierarchical method, Fuzzy Clustering, similarity measure, Linked Data

1. Introduction

The Linked Data movement has experienced exponential growth in terms of published data sets. Within two years, the number of triples has grown from 4.7 to 34 billion and therefore there is a lack of Linked Discovery techniques to find more and more links between knowledge bases. The task of a link discovery is to compare entities and suggests a set of entities whose similarity is above a given threshold. Clustering can decrease the number of comparisons before link discovery. Clustering is an important tool for analyzing data. Clustering is the process of grouping a data set in such a way that the similarity between data within a cluster is maximized while the similarity between data of different clusters is minimized. A number of clustering techniques have been developed, and these can be classified as hierarchical, partitional and density-based methods. Hierarchical techniques produce a nested sequence of partitions, which a single, all inclusive cluster at the top and singleton clusters of individual points at the bottom. Agglomerative and divisive are two types of hierarchical clustering methods [1]. Agglomerative clustering methods start with each object in a distinct cluster and successively merge them to larger clusters until a stopping criterion is satisfied. Alternatively, Divisive hierarchical clustering started with all objects in one cluster. It subdivides the cluster into smaller and smaller pieces, until each object forms a cluster on its own or until it satisfies certain termination conditions, such as a desired number of cluster is obtained or the diameter of each cluster is within a certain threshold. From another perspective, clustering algorithms can be classified into two categories, hard clustering and fuzzy clustering. While in hard clustering an entity belongs only to one cluster but Fuzzy clustering methods, allow the entities to belong to several clusters simultaneously, with certain degrees of membership. The memberships help us discover more advanced relations between a given entities and the disclosed clusters [2]. Related works that focus on Linked Data include Bizer et al[3] who presented a ”Multidimensional Blocking” for link discovery. This method is organized in three phases:

- Index generation
- Index aggregation
- Comparison pair generation

The overhead of” Multidimensional Blocking” is higher than that of standard blocking. The current known framework for link discovery on the Web is SILK. It provides a flexible, declarative language for specifying link condition. The weakness of SILK is that the recall is not guaranteed to occur [4]. In this paper, we present a hybrid clustering algorithm that combines the advantages of hierarchical clustering and fuzzy clustering techniques. Our algorithm cluster similar entities of data sets and reduce the number of comparisons before link discovery. Our approach is organized in two phases:

1. First based on feature selection principles, the properties of entities are selected. Then the entities are divided into two clusters by random initialization of cluster centers.
2. In the split phase, the worst cluster is determined and split. This stage is repeated until the optimal number of clusters is achieved.

The most important advantage of our approach is:

- The intelligent finding of the number of clusters.
- The ability to run on metric and semi- metric space.
- The consideration of the various types of entity properties.
- Less dependent on randomly chosen initial cluster centers.

The remainder of this paper is structured as follow: a formal definition for the problem is presented in section 2. We present the approach in Section 3 and report on the results of experimental evaluation in Section 4. We conclude with the discussion and an outlook on future work in Section 5.

2. Problem formulation

Given two relations with the same features *RA (f1, f2 …, ft)* and *RB (f1, f2 …, ft)*. A fuzzy matching function *FMF* takes as input triple ($r_A, r_B, \{\theta_1, \dots \theta_t\}$) and produces a fuzzy output {[0,1]} where:

- *rA* ∈ *RA* is an entity with attribute values *(rA(f1),…,rA(ft))* and *rA(f1)* ∈ *Dom(RA.f1), …, rA(ft)* ∈ *Dom(RA.ft).*
- *rB* ∈ *RB* is a record with attribute values *(rB(f1),…,rB(ft))* and *rB(f1)* ∈*Dom(RB.f1),…,rB(ft)* ∈ *Dom(RB.ft).*
- $\{\theta_1, \dots \theta_t\}$ are predefined similarity thresholds for the corresponding attributes *f1, … ft* in *RA* and *RB*.

The output of the fuzzy matching function *FMF* is decided based on:

$$FMF(r_A, r_B, \{\theta_1, \dots \theta_t\}) = \left\{ fuzzy\,num = avarage\left(g_i\left(r_A(f_i), r_B(f_i)\right)\right)\right\} \quad (1)$$

Where $g_i: Dom(R_A.f_i) * Dom(R_B.f_i) \rightarrow R^+, i = 1, \dots t$ are predefined similarity measures or distance functions defined over the domains of corresponding attribute *fi* for the relations *RA* and *RB.*

3. Approach

In this section, we present our model in more detail. Figure 1 gives an overview of the workflow. Our approach is organized in two phases: first, the division of data in two clusters; then the determination of the worst cluster and splitting. The number of clusters is unknown, but our algorithms can find this parameter based on the complexity of cluster structure.

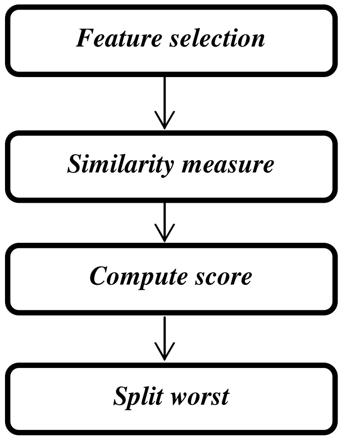

Figure 1. Workflow of approach

Initialization of clustering

Our approach is a branch of divisive hierarchical clustering. Divisive hierarchical clustering started with all objects in one cluster. It subdivides the cluster into smaller pieces, until each object forms a cluster on its own.

Feature selection

Clustering activity is based on feature selection. Feature selection is the process of identifying the most effective subset of the original feature to use in clustering. The best subset contains the least number of dimensions. Subset selection algorithms can be classified into Wrappers, Filters. A wrapper method evaluates the candidate feature subsets by the learning algorithm. In clustering, a wrapper method uses a clustering algorithm. Filter methods use an evaluation function that bases on properties of the data and is independent on any algorithm. Advantages of filter method are that they scale to high-dimensional datasets and they are computationally simple and fast but the wrapper methods have higher accuracy [5]. We use Wrapper method and evaluate the subset with an enhancement of fuzzy clustering.

Similarity measure

It is natural to ask what type of standards we should use to determine the closeness, or how to measure the distance or similarity between a pair of entities. Extracting features from entities is based on the domain of the datasets; a similarity measure is assigned to the features. Since datasets of linked data typically involve a variety of different data types, various similarity measures are defined. Most of the well-known clustering methods are implemented only for numerical data. The proposed clustering algorithm allows different types of data features such as numeric, symbolic and string data.

Numeric similarity:

The similarity of two numbers is computed with:

$$sim_{number}(x,y) = \begin{cases} 1 - \left(\frac{|x-y|}{max(x,y)}\right) & if\ x,y > 0\ \ or\ \ x,y < 0 \\ -\left(\frac{|x-y|}{max(x,y)}\right) & if\ x > 0, y < 0\ \ or\ \ x < 0, y > 0 \end{cases} \quad (2)$$

String similarity:

A number of string similarity measures have been developed and presented in the literature. We use the "Jaro-winkler"[6]:

$$Jaro(\sigma_1,\sigma_2) = \frac{1}{3}\left(\frac{c}{|\sigma_1|} + \frac{c}{|\sigma_2|} + \frac{c - t/2}{c}\right) \quad (3)$$

Consequently, the following function is defined:

$$\mathrm{sim}_{string}(x,y) = \mathrm{jaroalgoritm}(x,y) \quad (4)$$

Final similarity:

This function is the weighted average of the above similarity measures:

$$\mathrm{finalsim}(a,b) = \frac{(\mathrm{sim}_{number} * w_{num}) + (\mathrm{sim}_{string} * w_{string})}{w_{total}} \quad (5)$$

Initial cluster centers

The proposed method chooses two randomly- selected entities as the initial centers. After the initial cluster centers have been selected, each entity is assigned to the closest cluster, based on its distance from the cluster centers. For each clustering step, calculates membership matrix based on fuzzy clustering algorithm:

$$U_{i,j}^{t+1} = 1 \Big/ \sum_{l=1}^{c} \left(\frac{D_{l\,j}}{D_{i\,j}}\right)^{\frac{1}{1-m}} \quad (6)$$

For i=1,2,.....,C and j=1,2,.......,N
C is the number of cluster
N is the number of entities.
D is distance the two entities.

Fuzzy clustering methods, allow the entities to belong to several clusters simultaneously, with certain degrees of membership. The memberships help us discover more advanced relations between a given entities and the disclosed clusters [2].After this step, all entities are divided into two clusters. To continue in the next step, we need to find new centers. For this purpose the following steps are carried out:

a. To find the entities which have the highest similarity to their centers, the cluster members are sorted in descending order.
b. 20 percent of previously sorted entities are listed under t as "sim list".An average of the feature of entities of "sim list" is calculated. For numeric properties, the average number and for string properties, the LCS algorithm[18] is used.
c. Finally, a new cluster center is computed with:

$$center = \frac{(average(number) * w_{num})}{w_{total}} + \frac{(LCA(string) * w_{string})}{w_{total}} \quad (7)$$

The pseudo-code of the proposed algorithm is represented in Algorithm 1.

[1] Longest Common Subsequence

Input: cluster c with its entities
Output: new center.
Begin
Entities are sorted in descending order.
Simlist ← %20 sorted entities.
Wn ←weigh of numeric properties.
Wstr ← weigh of string properties.
Wsym ← weigh of symbolic properties
Calculate average;
Begin
***foreach** entities € simlist*
begin
anp ← average number properties (a,b)=a+b/2
astrp ← average string properties(a,b)=LCS(a,b)
end
end
*newcnetr=((anp*wn)+(astrp*wstr)/ total weight*
end.

Split cluster

The general idea in the splitting is to identify the "worst" cluster and split it, thus increasing the number of clusters one by one [7]. To find the worst cluster, point(i) is assigned to each cluster *i*:

$$point(i) = \frac{\sum_{k=1}^{n} U_{k\,i}}{n} \quad (8)$$

Small point (i) shows that cluster i is large and spare in distribution. Hence, the cluster which takes of minimum of point (i) will be the candidate for worst cluster.
Cluster **W** is identified to be split, supposing that the cluster center is C_0 and the number of clusters for each step is **C**. the algorithms for splitting can be formulated follows:

1. From among the entities of **W** the one labeled "not try" and has the lowest similarity with the **C-1** cluster centers is chosen and namedC_1.
2. The distance of all entities of **W** from C_0 andC_1 are calculated and the **W** cluster is split into W_0 and W_1 on basis of the calculated distance.
3. Calculate distance of each entities from C_0 andC_1. Then split cluster **W** into W_0 and W_1 based on calculated distance. C_1 Is assigned as the cth cluster center if $|W_1|/|W| > \%20(W)$ otherwise the label of C_1 should be changed to "try" and go to step 2.

After two steps, a new cluster is created. Step 1 and 2 are repeated with the reminding entities of **W** until C+1th clusters are found. The pseudo-code of the proposed algorithm is represented in Algorithm 2.

Input: cluster ***W***, centerC_0,
Output: new cluster W_0 and W_1
Begin
Find C_1
Begin
***Foreach** entities ∊ W*
C_0 → Entity has minimum distance with c-1 center and not tested.
End.

Spilt w
Begin
***Foreach** entities* $\in W$
Begin
dis1→ Calculate distance (e_i, C_0)
dis2→ Calculate distance (e_i, C_1)
***If** (dis1>dis2)*
$W_0 : \{e_1\}$
Else
$W_1 : \{e_1\}$
End.
If $|W_1|/|W| > \%20(W)$
Split W to W_0 and W_1
Else e_i *is tested.*
End.
***End**.*

The split worst cluster phase should be repeated until the optimal number of clusters is achieved. Choosing this parameter is a difficult problem. In each step of the algorithm, if the number of new cluster member is more than 20 percent of candidate cluster members, the split occurs. Based on the distribution, clusters broken or stops and the optimal number of clusters are obtained.

4. Evaluation

Datasets description

To prove the efficacy of the proposed approach, the performance of the clustering algorithm has been tested on three datasets of linked data: DBpedia, LinkedGeoData[19] and LinkedMDB datasets. DBpedia is a community effort to extract structured information from Wikipedia and to make this information available on the Web that currently contains more than 3.64 million resources[8]. Another dataset is LinkedGeodata that consist of 20 billion triples and the LinkedMDB database contains 3.5 million of RDF triples . We used a dataset consisting of 100,000 triples from DBpedia, 200,000 triples from LinkedGeoData for experiment 1 and 1000 triples from LinkedMDB and 1000 triple from DBPedia for experiment 2.

Performance Evaluation

Experiment 1: First, we interlinked places of DBpedia and LinkedGeoData datasets without the use of any clustering method. The result was $2 * 10^{10}$comparisons. Then, we evaluated how the clustering method reduces the number of comparisons. Table 1 summarizes the results. The evaluation shows that clustering reduces the number of comparisons by a factor of 142,857.

Table 1. Result of experiment1

Method	Comparisons
Full evaluation	$2 * 10^{10}$
Clustering	140,000

[2] http://www.linkedgeodata.org

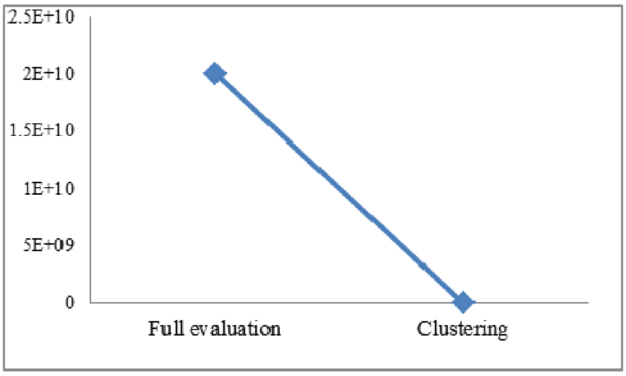

Figure 2. Decrease comparisons.

Experiment 2: The proposed model does not depend on any specific domain, so we evalute our model with the data sets on a different domain. In this experimnet, the movies of LinkedMDB and DBpedia data set are linked. Table 2 summarizes the results.

Table 2. Results of experiment 2

Method	Comparisons
Full evaluation	1000000
Clustering	900

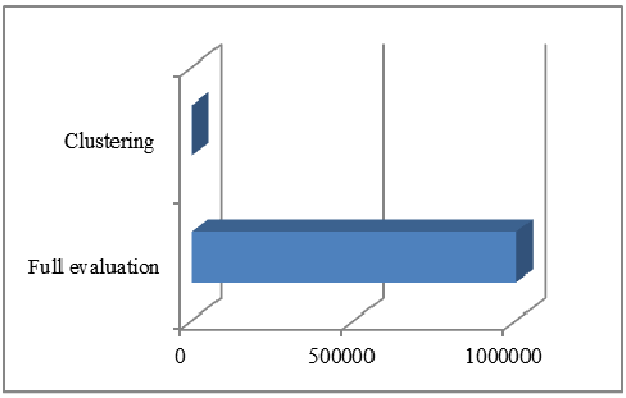

Figure 3. Different domain

Quality Evaluation

This section provides a summary of the quality evaluation of the implemented model. After clustering, each entities of datasets falls into one of the following groups:

- The entities which were recognized in same cluster and this recognition are correct.
- The entities which were recognized in same cluster but this recognition are incorrect.
- The entities which were recognized in different clusters but this recognition are incorrect and they are same in real.

In order to evaluate the quality of the interlinking LinkedGeoData and DBpedia, 500 place of LinkedGeoData which currently have correct owl:sameAs link to corresponded places in DBpedia are randomly selected. The results show that how many entities fall within each of the above defined groups.

Table 3. Interlinking between LinkedMDB and DBpedia

Type of group	count
Correct derived entities	475
Incorrect derived entities	25
Not- derived entities	25

The two most frequent and basic measures for information retrieval effectiveness are precision and recall.

Precision (P) is the fraction total of number detection similar entities that are true:

(9)

$$Precision = \frac{true\ detection\ entities}{detection\ entities} \quad (10)$$

Recall (R) is the fraction total of number similar entities that are true detection:

$$Rceall = \frac{true\ detection\ entities}{total\ entities} \quad (11)$$

Results from Table 4 and equations 9, 10 shows that the precision is %100 and recall is %95.

Our algorithm is an efficient clustering algorithm has some features that are mentioned in Table 4.

Table 4. Feature of our algorithm

Features	Y/N
Scalability	Y
Ability to cluster different types of attributes	Y
Ability to discover clusters with different shapes	N
Minimal input parameter	Y
Not sensitive to noise	N
Insensitive to the order of input records	Y
Ability to handle high dimensionality	Y

We explained the following two central evaluation questions:

- What is the best number of cluster?

Different performances of the tests indicate the number of clusters depend on the data sets and dispersal of their members is between $\sqrt{N}/_2$ and $\sqrt{N}$.

- Does the initial selection of centers affect the result?

The proposed algorithm was run with different initial centers and results show a random selection of centers does not affect the final results.

5. Discussion and Future Work

In this paper, we propose a new hybrid algorithm, which combines the features of fuzzy algorithm and hierarchical algorithm. Our algorithm decreases the number of comparisons on link discovery. Using hierarchical algorithm in the first level, the data is divided into two groups. In the second level the worst cluster is determined by matrix memberships and then it split. This stage is repeated until the optimal number of clusters is achieved.Creating typed links, between the entities of different datasets is one of the key challenges on web of data .We presented the clustering approach, which decreases the number of comparisons on link discovery. The results of linking the movies in LinkedMDB to corresponding movies in DBpedia and also linking the places in LinkedGeoData to the places of DBpedia show the it reduces the number of comparisons without loss of recall and precision. Hopefully in the future, we will be able to elevate the proposed method recall to 100 % using the membership matrix.

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