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Towards New Optimized Artificial Immune Recognition Systems under the Belief Function Theory

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Abstract

Artificial Immune Recognition Systems (AIRS) are powerful machine learning techniques, which aim to solve real world problems. A number of AIRS versions have produced successful prediction results. Nevertheless, these methods are unable to handle the uncertainty that could spread out at any stage of the AIRS approach. This issue is considered as a huge obstacle for having accurate and effective classification outputs. Therefore, our main objective is to handle this uncertainty using the belief function theory. We opt also in this article for an optimization over the classical AIRS approaches in order to enhance the classification performance.

1 Introduction

Artificial Immune Recognition System (AIRS) [Watkins and Boggess, 2002] is considered as one of the most efficient machine-learning algorithms inspired by the immune system metaphors. It had gained wide popularity among machine learning approaches due its high efficiency in attempting great and competitive classification results. Many AIRS versions have been proposed in the 2000s. A new AIRS3 [Jenhani and Elouedi, 2014] version have been introduced showing a huge improvement in term of classification accuracy. Nonetheless, this approach does not deal with the uncertainty emerging at the various levels of the classification process, which may seriously decrease the prediction performance. In order to enhance the classification efficiency, we propose in this research work to handle the uncertainty using the belief function theory and to optimize the tradition AIRS3 by employing different optimization techniques such as the gradient descent and the genetic algorithm.

2 Belief Function Theory

The belief function theory [Dempster, 1968; Shafer, 1976] is one of the most popular theories for handling uncertainty. The frame of discernment denoted by Ω represents the set of n elementary events such that: $\Omega = \{\Omega_1, \Omega_2, \cdots, \Omega_n\}$. It includes hypotheses about the given problem. The power set of Ω, denoted by 2^Ω, contains all the possible values that can be taken by each subset of Ω. The mapping function $m : 2^\Omega \rightarrow [0, 1]$ represents the basic belief assignment (bba) defined by $\sum_{E \subseteq \Omega} m(E) = 1$ where $m(E)$ is the basic belief mass (bbm) stating the piece of belief specifically dedicated to the event E.

The combination of two given bba's m_1 and m_2 obtained from two different sources of uncertainty information can be achieved via Dempster's rule of combination determined by: $(m_1 \oplus m_2)(E) = k. \sum_{F,G \subseteq \Omega: F \cap G = E} m_1(F) \cdot m_2(G)$ $where$ $(m_1 \oplus m_2)(\emptyset) = 0$ and $k^{-1} = 1 - \sum_{F,G \subseteq \Omega: F \cap G = \emptyset} m_1(F) \cdot m_2(G)$. For the making decision, beliefs can be transformed into a pignistic probability denoted by $BetP(E)$ and the hypothesis with the highest value is selected. $BetP(E)$ is defined as:
$BetP(E) = \sum_{F \subseteq \Omega} \frac{|E \cap F|}{|F|} \frac{m(F)}{(1-m(\emptyset))}$ $for\ all\ E \in \Omega$.

3 Artificial Immune Recognition System

AIRS is a supervised learning algorithm inspired by the natural immune system. Data in AIRS approaches represent antigens and antibodies having identical representation. The first step is data normalization and distance computation. Then, an initiation of the memory cell (MC) pool and the ARB pool is performed. After that, a selection of the best memory cell is carried out based on the computed stimulation between all the antigens in the MC pool sharing the same class. In fact, the cell with the high stimulation value is considered as the best match memory cell. This latter will be cloned and its clones are included in the ARB pool. Therefore, a selection of the candidate memory cell is performed. This cell is considered as the ARB with the maximum stimulation value. Thus, the MC pool is updated. Accordingly, the K-Nearest Neighbors (KNN) method is applied and the accurate output is selected relying on the major vote of K closest antigens. An improved version called AIRS3 have been suggested in [Jenhani and Elouedi, 2014] where a computation of the number of represented antigens ($numRepAg$) for each obtained memory cell in the MC pool is performed. The K value used in the KNN technique is no more the number of neighbors but it becomes the sum of $numRepAg$ of all the selected cells. Finally, a calculation of the sum of $numRepAg$ of all the picked cells with the same class label is achieved and the antigen having the highest sum is selected as the new unlabeled antigen.

4 Contributions

During our research work, we aim to keep improving the AIRS techniques by enhancing the classification performance and achieving the most accurate results. We attended successfully our purpose by innovating impressive new AIRS approaches. To start with, we had proposed an evidential AIRS3 named EAIRS3 [Abdelkhalek and Elouedi, 2020a], in order to deal with uncertainty and handling the total ignorance. In our approach, we employed the belief function theory as a flexible and rich environment allowing us modelling and combining several pieces of evidence. So that, during the classification process, we employed the Evidential K-Nearest Neighbors $EKNN$[Denoeux, 2008] where various belief functions mechanisms are included. At this stage, the new component introduced in AIRS3 called $numRepAg$ is not taken into account and all antigens in the MC pool are treated with the same relevance. In order to solve this problem, we had suggested a new weighted evidential AIRS3 called WE-AIRS3 [Abdelkhalek and Elouedi, 2020c] where we consider the weight of each obtained memory cell in the MC pool and where we employ the weighted $EKNN$. In other words, we generate weighted basic belief assignments (bba's) and we aggregate it relying on Dempster's rule of combination. Such process depends highly on different parameters that could affect the classification performance. So that's why, the main objective of our next contribution was to find the optimal or near-optimal values of these parameters and increase the prediction efficiency. In fact, optimization is considered as an important challenge in real world applications and several optimization strategies have been established. In [Abdelkhalek and Elouedi, 2020b], we opt for the gradient descent as a powerful and robust optimization method. We computed the cost function and minimized the error rate of the classification under the belief function framework. Carrying on with optimization theories, we proposed in [Abdelkhalek and Elouedi, 2021] to involve one of the most popular optimization techniques, which is the genetic algorithm. So that, a new Optimized EAIRS-GA was born. In this approach, we aimed to remove the randomness and reduce the number of parameters within the evidence theory. Our proposals have shown excellent results over the other traditional AIRS approaches. Results and experimental comparisons can be obtained in [Abdelkhalek and Elouedi, 2020a; Abdelkhalek and Elouedi, 2020c; Abdelkhalek and Elouedi, 2020b; Abdelkhalek and Elouedi, 2021].

5 Ongoing-Works and Challenges

Based on the accomplished work and the obtained results, we keep contributing to research in this domain and developing new AIRS approaches under the belief function framework. Recently, we have improved our last research work by adapting a new feature selection technique within an uncertain environment. In fact, our main goal is to emphasize the classification performance by reducing the number of feature and selecting only the relevant ones. The obtained results prove that implementing a preprocessing data phase to the optimized evidential AIRS approach improve the prediction performance and increase the classification accuracy.

6 Conclusion and Future Works

In our research work, we have suggested various AIRS approaches where the uncertainty has been considered. It would be interesting to emphasize the prediction efficiency and innovate more optimized evidential AIRS approaches. This could be realized by relying on different bio-inspired algorithms such as the particle swarm optimization (PSO) technique.

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