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Review of Different Strategies for Coordinative Planning of Multi-agent Systems

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ABSTRACT

Agent-based systems have been widely examined in the literature for various type of tasks. Within this examination, various strategies and modeling have been employed. Several surveys and reviews have been depicted in the literature regarding agent-based systems. However, minimal efforts have been made in the context of feature extraction and feature selection. This paper aims to review the strategies used for feature extraction and selection agent-based systems. In terms of the nature of agent communications, this paper tackles two types, centralized and decentralized. In terms of the workflow, this paper tackles three types, including coordinative, collaborative and emergent-based systems. Finally, a discussion is presented comparing the strategies and the frequent use of the strategies in the literature. Based on this review, most of feature extraction agent-based systems rely on either coordinating or emergent-based strategies, while feature selection agent-based systems rely on collaborative strategies. However, there are several aspects that we can consider to be classify agent-based strategies. This review develops a classification scheme for systems used for specific tasks, including feature extraction and feature selection.

Key words: Agent-based System, Intelligent Agent, Multi-Agent System, Feature Extraction, Image processing, Texture Descriptor, Intrusion detection, Text Analysis

1. INTRODUCTION

Multiagent systems (MAS) are part of a growing research area in artificial intelligence that aims to formulate complex systems that contain several agents and a method that describes the interactions among the individual behaviors of these agents [1]. Despite that there is no standard definition for MAS, an agent can be represented as a robot that has a goal, action and domain knowledge. An agent system is a computerized system that consists of multiple interacting agents within an environment. Such a system can be used to handle problems that are difficult to solve using an individual agent. The system could have a set of rules that intend to solve specific problem or could have evolutionary algorithms that seek to find better solutions for NP-hard problems [2].

However, regarding the limitations of an agent-based system that can be represented as the individual behavior of agent, multiagent systems have been proposed to consider the collective behavior of multiple agents. Multiagent systems are an artificial intelligence application that intends to construct a complex system that contains multiple agents, which requires the coordination of the collective behavior of the agents and the corresponding individual behavior. The agent might be an entity that has a goal, performs actions or so-called behaviors, and has domain knowledge [3].

Agents are entities that are intended to observe specific events and respond with an appropriate action to accomplish a particular goal [4]. Such observed events might be physical or virtual events in which the agent can relate the events to the desired goal. There are several factors that distinguish the agents from traditional object-oriented methods. First, unlike objects, agents have more control over their own behavior. Second, the nature of agents is based on a multithreaded scheme, which does not always exist in objects. Another characteristic of agents is autonomy, which indicates the ability of these agents to find a solution to a particular problem by themselves without any interventions. This behavior is known as “self-organized” behavior. Note that autonomy is different than the automatic; the latter refers to a predefined set of rules that determine the actual response, and autonomy refers to the flexibility of the multiagent system in which the responses rely on specific actions [5].

Agent-based systems have been used for various tasks, commonly feature selection, where the aim is to determine most accurate features or characteristics for a particular domain of interest. To the best of our knowledge, there has been no comprehensive review of agent-based systems for feature extraction and selection tasks in which strategies and modeling are discussed. Therefore, this paper attempts to conduct such review.

This paper is organized as follows. Section 2 provides a brief background regarding feature extraction and selection tasks along with agent-based strategies and modeling used for such tasks. Section 3, Section 4 and Section 5 tackle each strategy individually with the related work of the strategy. Finally, Section 6 gives a discussion where all the strategies are compared and analyzed.

2. FEATURE EXTRACTION AND SELECTION

Feature extraction and selection tasks are widely examined in the literature, where the aim of such tasks is to reduce the dimensionality of data representation. Obviously, reducing the dimensionality requires the determination of the significant and insignificant features to consider the significant features and ignore the insignificant features. Discarding the insignificant features to directly reduce the space has an essential role in improving both the efficiency and effectiveness of various tasks such as classification, prediction and outlier detection. However, the context of feature selection varies depending on the domain addressed within such tasks.

For example, in the area of image processing and computer vision, the texture indicates the duplication of basic texture elements called texels. Such an element consists of multiple pixels that are either intended to be placed randomly or in a periodic manner. According to [6] an image texture can be coarse, fine, smooth, granulated, rippled, regular, irregular or linear. Generally speaking, the texture reflects the neighbor-surrounding points the same way that a color reflects a point value [7]. In this vein, the scale is a significant factor that is associated with the texture in which a variant scale leads to variant textures even if the textures are equivalent [8]. There are several methods that have been used in the literature regarding texture analysis including statistical, structural, model-based, and signal processing [9]. To represent the texture, which usually articulated numerically, one of the aforementioned methods should be used. Representing the texture of an image can be seen as feature extraction in which the features of the image are exploited for further tasks such as classification and recognition. Apparently, the variety of image features means that a single feature fits a specific application but not all applications. Therefore, the process of identifying the most suitable features for specific problems is a challenging task. One of the common obstacles during the process of determining texture values for certain images is how to examine the invariant properties in the descriptors. Such variations could occur in the texture appearance or scale, which definitely leads to variations in the texture properties.

On the other hand, intrusion detection is an interesting research area that has caught attention in the last decade. This area of study investigates abnormal activities that occur on a network [10]. There are various types of threats that can be encountered in any network such as denial-of-service (DoS), probing, Trojan horses, worms and viruses [11]. Within the investigation of such abnormal activities, specific features are exploited. These features are related to the connection characteristics such as the duration and sizes of sending and receiving packets. Plenty of features can be examined under such characteristics. In this regard, researchers have intended to apply different feature selection techniques to identify the most accurate features that discriminate the occurrence of intrusions.

Finally, domain of text analysis has been extensively examined in terms of feature selection. In such a domain, specific data representation is used such as N-gram or bag-of-words (BOW); these representations are intended to articulate the distinctive or most frequent terms. Therefore, the feature space can be represented by terms, and researchers in the literature have accommodated a wide range of feature selection tasks to determine the significant terms or features in this context.

Apparently, an agent-based system can appropriately fit the task of feature selection where the agents articulate the role of features. In this paper, an extensive review is conducted to explore the strategies and modeling used for the agent-based feature selection systems depicted in the literature. The paper is organized as follows. Section 2 highlights the general strategies and modeling used for agent-based systems. Section 3 discusses agent-based feature extraction, while Section 4 reviews agent-based feature selection. Section 5 provides a discussion and comparison of the related works. Finally, Section 6 provides conclusions.

2.1 Strategies

There are differences among multiagent systems based on the strategies of the systems. Three main categories have been identified in the literature based on the strategy used within the interaction among the agents; these categories are coordinated MAS, cooperative MAS and emergent-based MAS [12]. The following subsections illustrate each of these categories.

Centralized: This type of agent works in a centralized manner in which one or two agents have the ability to take the role of the coordination or communications can occur between the agents themselves [13]. This type of agent consists of two main strategies:

- **Coordinated/Cooperative Agent-based:** In this multiagent system, the strategy is based on the coordination and interaction of the agents toward accomplishing a coherent goal. In this case, one response of a particular agent is significantly considered by the other agents during planning and execution. The communications between the agents are performed using one or two agents, also known as the mediator and facilitator.

- **Emergent-based Agent:** This type of multiagent system presents collective behavior in which the individual agents have simple rules to perform simple tasks; the collected behavior of all agents is intended to perform sophisticated and complex task. The action of an individual agent is predictable and easy to explain; however, the holistic action of all the agents is not predictable and not easy to explain. This type of MAS simulates certain biological behaviors such as an ant colony and a swarm of birds. The communications between the agents in this strategy are performed by the whole of the agents, where every agent has information about the other agents.

Decentralized: This type of agent works separately without any kind of coordination [13]. Usually, this type of agent is used for competitions where the aim is to identify the best solution or most efficient mechanism. This agent consists of the following strategy:

- **Collaborative/Competitive Agent-based:** In this multiagent system, the agents apply a competitive behavior to accomplish the goal. Usually, this type of system consists of agents that have divergent or antagonistic workflows and goals. Assuming a set of agents with different capabilities in terms of achieving higher classification or recognition accuracy, the goal is to acquire the maximum accuracy achieved by one or two agents due to the variances in the capabilities leading to variances in the accuracies.

2.2 Modeling

In a multiagent system, every agent is intended to apply a specific operator with differing costs, which leads to an increase the complexity of the problem that is being solved. Therefore, several studies attempted to propose various models for centralizing the workflow of the agent system to determine the optimal processing in accordance with both time and cost constraints. Ephrati & Rosenschein [14] presented two main models that can be illustrated as follows:

- **Divide-and-Conquer Model:** The decomposition of a specific task into multiple subtasks significantly decreases the time and cost complexity. In this scenario, the problem is divided into several subproblems, and each agent contributes toward solving a specific sub-problem. Consequentially, a merging process occurs to combine the solutions produced by all the agents that corresponds to solving the global problem. It is apparent that this type of model is used with coordination and emergent-based strategies where the main goal is divided into subproblems to reduce the complexity.

- **Ranking/Filtering Model:** A task with multiple agents carries out different operators. Each operator has a performance different than those of the others. In this case, the ranking model aims to find out which agent is the most capable of performing the task. A pre-processing task is accommodated to identify the most suitable agent that has the operator that satisfies the minimum complexity constraints. It is clear that this type of modeling is used with a collaborative strategy where a contest is conducted between the agents to identify the best agents. In this regard, ranking or filtering is needed to determine the most accurate agents.

3. AGENT-BASED FEATURE EXTRACTION

In In this section, a review of the agent-based systems that have been used for the sake of feature extraction is discussed. This discussion aims to identify the strategies and modeling used within these studies. Different domain of interests are involved.

First, in the domain of image processing, Yanai [15] has proposed a multiagent system for recognizing 3D objects in a real scene. The system aims to exploit primitive information such as lines, edges or regions using various algorithms. Every agent is located on the image and builds a set of coherent primitives called a representation. This representation is compared with a database to identify a potential object in the scene. Consequentially, the agents interact to negotiate the local representations. Communications between agents make the representations evolve to find common coherent representations. The system reaches its goal (object recognition) when all the agents agree on the representation. From the communication between the agents and the mechanism of the workflow, it is clear that this study used the centralized coordinated agent-based strategy along with divide-and-conquer modeling.

Boucher [16] used an agent-based system for the segmentation and the interpretation of sequences of cytological images. The proposed method is a distributed approach where each agent is specialized in recognition of a concept in the image. In this regard, this work can be classified as centralized coordinated with divide-and-conquer modeling.

Mazouzi et al. [17] proposed an adaptive multiagent system that enables the emergence of edge detection on pictures representing 3D scenes. The proposed system uses multiple algorithms for the segmentation process. The system is able detect emerging contours. From the distributive and emerging characteristics, this study can be classified as a centralized emergent-based strategy where the divide-and-conquer modeling is used.

Maleš et al. [18] proposed an agent-based system for the task of face recognition. The proposed system used different deep learning techniques to extract significant features from the facial images. The extraction of such features has been performed via a centralized, coordinated divide-and-conquer manner.

Chitsaz & Seng [19] proposed a multiagent system for medical image segmentation. The original image is divided into a set of subimages. The authors used two hierarchical levels; local and global. At the local level, each local agent works on a subimage. The agent aims to mark each pixel as a specific zone using a priori knowledge. At the global level, the agent builds a final segmented image by receiving the results of all the agents' work. From the workflow of the agents in this study, the system can be categorized as a centralized emergent-based strategy with divide-and-conquer modeling.

In the field of intrusion detection, Bakar et al. [20] presented an agent-based intrusion detection system based on a rough set classification that uses simple agents. The proposed agents were intended to generate rules from a large dataset. Such rules were specifically designed to articulate the noise and uncertainty in the data. Examining the effectiveness of the rules requires certain sort of coordination; therefore, this system can be classified as a centralized and coordinated divide-and-conquer strategy.

Similarly, Zhu et al. [21] proposed a multiagent system for intrusion detection. The agents designed were intended to learn network-based audit data and host-based audit data. The learning mechanism was conducted using association rules, which allowed the agents to learn from predefined rules. Similar to a previous study, the examination of the rules requires coordination; thus, this system can be categorized as coordinated agent-based system.

Xiantai et al. [22] proposed a multiagent system for detecting worms within a network. The agents are designated to articulate the occurrence of worms and the related threats such as distributed denial of service. The agents in this study can be categorized as a coordinated strategy.

Jin et al. [23] proposed an agent-based system for intrusion detection in wireless sensor networks. The agents are employed in the cluster heads of the sensors to identify the features of the activities interacting within the network. Since there is a cluster head, this system can be considered as a coordinated agent.

In the field of text analysis, Lee et al. [24] proposed an intelligent agent system for summarizing Chinese electronic news. The proposed agent system was intended to examine the parts-of-speech of Chinese words and then identify the most significant tags, which are maintained within the summarization process. This type of examination requires emergent extraction; therefore, the agent in this study can be classified as emergent-based.

In the same regard, Gentili et al. [25] proposed an intelligent agent system for the classification of text documents. The authors used web documents along with a wide range of features such as HTML tags. In this regard, the proposed system examines the most accurate features that incorporate document classification. On the other hand, a bag-of-words feature is sometimes used to classify the text document, where all the terms inside the documents are represented as attributes in the process of classification. However, examining large numbers of terms in the context of attributes contributes toward increasing the dimensionality, which poses a demand for feature selection to reduce the dimensionality. The agent in this study can be classified as emergent-based.

Finally, Hennig et al. [26] proposed an intelligent agent system for text summarization. This system is based on an ontology that articulates the tree of concepts. In this regard, the authors used the system to process massive texts and extract each sentence. The extracted sentences are mapped with a concept from the ontology and summarized. The agents in this study can be categorized as coordinated.

4. AGENT-BASED FEATURE SELECTION

This This section aims to review the state of the art in terms of agent use for feature selection tasks. In the field of image processing and segmentation, Remagnino et al. [27] proposed a multiagent system that aims to detect objects within dynamic scenes. The proposed system uses each agent to analyze specific scene. In addition, the system uses a Bayesian network to deduce one semantic of the movements of the various objects. For every object in the scene, an agent of behavior is created to operate at the object level. From the behavior of the agents in this study, this system can be classified as decentralized with ranking modeling.

Ramos & Almeida [28] proposed a reactive multiagent system that uses a metaheuristic approach of ant colony for gray image segmentation. The system showed collective perceptive capacity from the interactions between the agents and the interactions between the agents and the environment. Since the agents in this study mimic natural swarming behavior, this type of system tends to be an emergent-based strategy. However, the aim was to identify best way to segment gray images; thus, the modeling is ranking.

Liu & Tang [29] proposed a reactive multiagent system for brain MRI segmentation. These researchers claimed that using agents is more efficient than the classical region-based algorithms. The pixels are labeled by four types of agents according to belonging to a region. The local perceptions of the agents guide the actions of the agents. However, the agents in this study can be classified as a collaborative ranking strategy.

Richard et al. [30] proposed a hierarchical system of multiagents for image segmentation of brain Magnetic resonance imaging (MRI). The authors have used three types of agents that operate at three control levels: global control agents, local control agents, and tissue dedicated agents. The variety of levels makes the agents seem to be a collaborative ranking strategy.

Zhang & Nebel [31] proposed an intelligent agent for human face recognition under different dim light conditions. An intelligent agent helps in perceiving an environment where the captured faces are subject to different illumination conditions and acts upon that environment, which can be described by an intelligent approach toward integrating various techniques for the agent to perceive illumination, including normalization, feature extraction and classification. The illumination normalization technique is useful for removing dimness and shadow from a facial image, which reduces the effect of illumination variations while still retaining the necessary information of the face. The robust local feature extractor, which is a gray-scale invariant texture called local binary pattern (LBP) is helpful for feature extraction. The K-nearest neighbor classifier is used for the purpose of classification and matching the face images from the database. Thus, the agent tends to identify the input face image from the available database after preprocessing the image and feature extraction. Various images from the Yale-B database were used for testing to achieve this face recognition system. From the work mechanism, this study can be categorized as a collaborative ranking agent-based system.

Mahmoudi et al. [32] proposed a multiagent method for object recognition within urban areas. The proposed method used the features of WorldView-2 satellite imagery and a digital surface model. The authors first applied a preprocessing task to the dataset that is considered to be the information gathered from the satellite. In the first operational level of the proposed multiagent system, various kinds of object recognition agents modify the initial classified regions based on the spectral, textural and 3D structural knowledge of the agents. Then, in the second operational level, 2D structural knowledge and contextual relations are used by the agents for reasoning and modification. The agents in this study can be considered to be collaborative ranking agent-based.

Gonçalves et al. [33] proposed a texture descriptor method based on multiagents called crawlers regarding the limitations behind the existing texture analysis represented by the restricted capability of capturing the detail richness of the image surface. In this vein, the authors proposed a multiagent method based on an artificial crawler that enables interaction between the agents and the environment. In addition, the authors used the Minkowski method to improve the discriminatory power using the fractal dimension. The agents in this study can be considered to be collaborative ranking agent-based.

In the intrusion detection domain, Tsang and Kwong [34] proposed an agent-based system for intrusion detection for large networks in industrial plants. The agents are designed based on an ant colony algorithm where each agent mimics the behavior of an ant. The agents are intended to accommodate clustering tasks for the connections to identify the intrusive tasks. The agents in this study can be considered to be collaborative ranking agent-based.

Tsang et al. [35] proposed an agent-based system based on a multiobjective genetic algorithm for intrusion detection. The proposed method was intended to identify the most accurate set of features that satisfies both the accuracy and time consumption of intrusion detection. For this purpose, the authors used a wide range of network traffic features. The agents in this study can be considered to be collaborative ranking agent-based.

Gong et al. [36] proposed a multiagent system for detecting intrusions in an industrial control system. The proposed method was intended to play the role of feature selection in which the agents resemble the network traffic features. In this regard, a collaborative multiagent system was designed to identify the most accurate set of features. The proposed method was compared against traditional feature selection approaches such as information gain (IG) and chi-square. The results showed that the proposed collaborative multiagent system has superior performance in terms of determining the best features of intrusions. The agents in this study can be considered to be collaborative ranking agent-based.

Lin et al. [37] proposed an intelligent agent system for intrusion detection based on multiple classification methods. The proposed system uses two machine learning classifiers including support vector machines (SVMs) and decision trees (DTs). Along with the classification methods, a feature selection approach of simulated annealing (SA) was used to determine the best network traffic features. The proposed system examined the use of SA along with SVMs and DTs to find the optimal accuracy for detecting intrusions. The results showed that the combination of DT and SA outperforms the combination of SVM and SA in terms of detection accuracy. The agents in this study can be considered to be collaborative ranking agent-based.

In the domain of text analysis, Abbasi [38] proposed an intelligent agent system for the feature selection task in sentiment classification. The authors used the bag of words feature, where most of the terms occurring within the opinions are used. Consequentially, the authors used multiple feature selection approaches such as information gain, log likelihood and chi-square. In this regard, the proposed agent system identifies the best results for feature selection by the aforementioned approaches. The agents in this study can be considered to be collaborative ranking agent-based.

Aghdam et al. [39] proposed an agent-based system for feature selection in text categorization. The proposed method uses the bag-of-word feature and uses an ant colony algorithm to examine each term separately in terms of the accuracy of text classification. In this regard, each agent resembles the behavior of an ant within the search for the best features or terms. The proposed method was compared against traditional feature selection approaches such as chi-square and showed superior performance. The agents in this study can be considered to be collaborative ranking agent-based.

Ali et al. [40] proposed an agent-based system for the task of ontology enrichment. The agents were employed in a collaborative manner in which each agent attempts to enrich the text with accurate synonyms. Similarly, Jelokhani-Niaraki [41] used a collaborative multiagent system to improve the ontology enrichment in text expansion problems. The agents in this study can be considered to be collaborative ranking agent-based.

5. DISCUSSION

In this section, a discussion is provided for all the studies that have been mentioned for every strategy. Within this discussion, the domain of interest, the task (whether feature extraction or feature selection), strategy, centralization and modeling is identified for each study. Table 1 shows a summary of these studies.

Table 1: Summary of the studies

Study	Domain	Task	Strategy	Centralization	Model
Yanai [15]	Image Processing	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Boucher [16]	Image Processing	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Mazouzi et al. [17]	Image Processing	Feature Extraction	Emergent-based	Centralized	Divide-and-Conquer
Maleš et al. [18]	Image Processing	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Chitsaz & Seng [19]	Image Processing	Feature Extraction	Emergent-based	Centralized	Divide-and-Conquer
Bakar et al. [20]	Intrusion Detection	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Zhu et al. [21]	Intrusion Detection	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Xiantai et al. [22]	Intrusion Detection	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Jin et al. [23]	Intrusion Detection	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Gentili et al. [25]	Text Analysis	Feature Extraction	Emergent-based	Centralized	Divide-and-Conquer
Lee et al. [24]	Text Analysis	Feature Extraction	Emergent-based	Centralized	Divide-and-Conquer
Hennig et al. [26]	Text Analysis	Feature Extraction	Coordination	Centralized	Divide-and-Conquer
Remagnino et al. [27]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Ramos & Almeida [28]	Image Processing	Feature Selection	Emergent-based	Centralized	Ranking
Liu & Tang [29]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Richard et al. [30]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Zhang & Nebel [31]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Mahmoudi et al. [32]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Gonçalves et al. [33]	Image Processing	Feature Selection	Collaboration	Decentralized	Ranking
Tsang and kwong [34]	Intrusion Detection	Feature Selection	Collaboration	Decentralized	Ranking
Tsang et al. [35]	Intrusion Detection	Feature Selection	Collaboration	Decentralized	Ranking
Gong et al. [36]	Intrusion Detection	Feature Selection	Collaboration	Decentralized	Ranking
Lin et al. [37]	Intrusion Detection	Feature Selection	Collaboration	Decentralized	Ranking
Abbasi [38]	Text Analysis	Feature Selection	Collaboration	Decentralized	Ranking
Aghdam et al. [39]	Text Analysis	Feature Selection	Collaboration	Decentralized	Ranking
Ali et al. [40]	Text Analysis	Feature Selection	Collaboration	Decentralized	Ranking
Jelokhani-Niaraki [41]	Text Analysis	Feature Selection	Collaboration	Decentralized	Ranking

As shown in Table 1, it is sometimes difficult to differentiate between the coordination and emergent-based strategies since the workflows of these strategies are relatively similar. Therefore, the studies that used such strategies also used the divide-and-conquer model. The aforementioned strategies are mostly used with a feature extraction task.

On the other hand, the collaboration strategy is usually accompanied with a ranking model. This combination of strategy and model is mostly used for feature selection, which makes sense since the workflow of this strategy is based on a contest between the agents to determine the best agents. This idea is the core of the feature selection task. Fig. 1 represents the distribution of strategies in accordance with all the studies.

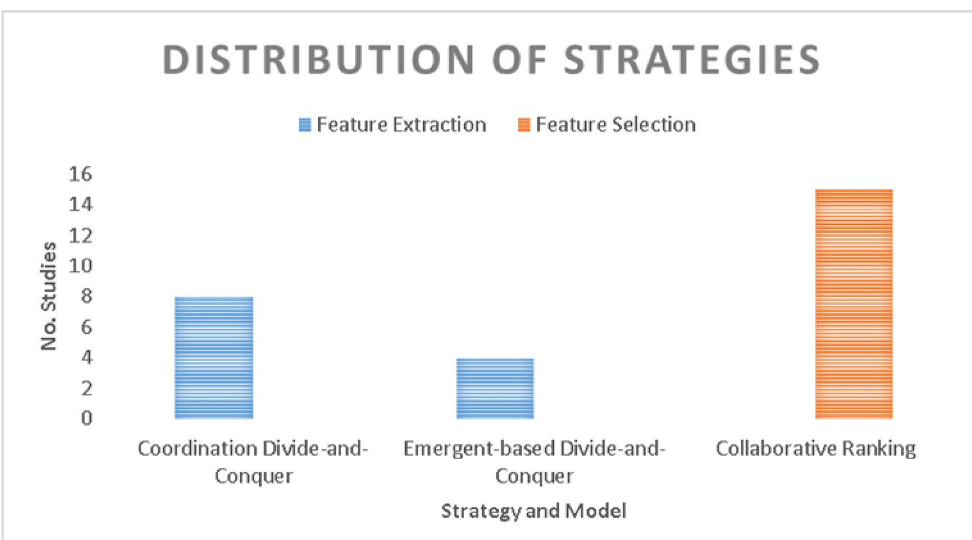

Figure. 1: Distribution of the strategies of the studies

6. CONCLUSION

This paper provides an extensive review of the strategies and modeling of feature extraction and selection agent-based systems. Both the coordination and emergent-based strategies are accompanied by feature extraction tasks, while the collaboration strategy is accompanied by feature selection tasks. For future work, reviewing the strategies of agent-based systems used for further applications would provide more insight for standardizing the strategies.

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