

RESEARCH ARTICLE

Ontology-Based Emotional Decision-Making in Self-Evolving Defensive Agents

RENDHIR R. PRASAD^{1,2} AND CIZA THOMAS³¹Department of Information Technology, Government Engineering College Barton Hill, Thiruvananthapuram, Kerala 695016, India²Department of Electronics and Communication Engineering, College of Engineering, Trivandrum, A. P. J. Abdul Kalam Technological University, CET Campus, Thiruvananthapuram, Kerala 695016, India³Directorate of Technical Education, Government of Kerala, Thiruvananthapuram, Kerala 695023, India

Corresponding author: Rendhir R. Prasad (rrp.jan26@gmail.com)

ABSTRACT Responding instantaneously in an unprecedented situation is inevitable to mitigate zero day attacks in the cyber world. This situation has strong resemblance with the fight for survival in biological world. Both being complex systems, the biological world and the cyber world have structural similarities. Emotions are the key factor used by biological beings to take intuitive decisions, which are key to survival in the natural world. Inspired from the idea of emotional decision making in natural world and the structural similarity shown by biological and cyber worlds, this paper proposes an ontological mechanism to implement artificial emotion-based decision making for autonomous agents in cyber security scenario. Emotions are modelled as manifestation of the goals of agents. Stimuli and response are connected through emotions using the ontological structure. The mechanism is proven useful in eliciting appropriate response for the stimuli using ontological reasoning through SPARQL queries.

INDEX TERMS Artificial emotion, complex systems, self-evolving systems, emotional decisions, ontology.

I. INTRODUCTION

It has been a major challenge to the artificial intelligence community and cyber security community to design systems that can self-evolve to meet the challenges posed by ever changing issues in cyber world. The data intensive models like deep learning techniques in machine learning are enthusiastically welcomed recently by the community. These techniques with ever increasing processing power and availability of data processing capabilities have increased the capability to analyse patterns and predict the future patterns. The patterns are the temporal patterns present in the network traffic. However, the challenge that still prevails is to make decisions in situations where the availability of the previous data is limited and time critical response is needed [1]. An example is the case of zero day attacks in cyber security scenario where totally novel attacks wreck havoc without getting detected. If we analyse the recent incidents of cyber attacks, this has been the major strategy of the attackers. The parallels of this situation can be found in other biological and social situations too. Even in the case of COVID19, a novel virus is causing considerable damage. This situation calls for the capability

of making intelligent and wise decision by analysing the previous patterns and also achieving the ability to instantly respond to attack. It can be seen that species develop substantial capabilities in fight for survival and adapting to the situation. In order to survive, biological beings strongly depend on intuitive decision making and capability to evolve in order to respond to novel challenges. The cyber security scenario shows striking resemblance to the situation of fight for survival in biological ecosystem. It can be seen that both biological systems and cyber security systems are complex systems, which show structural similarities [2]. Taking inspiration from this idea, we propose a mechanism that intuitively and instantaneously responds to cyber security threats. We start with the characteristics of complex system in general in order to investigate the underlying common characteristics shown by constituents of complex systems. The phenomenon of emotion from the perspective of complex system is defined further for exploring the possibility of modelling emotion to simulate emotion-based decision-making.

This work is inspired by the following research questions:

- What are the possible insights drawn from the structural similarity between complex systems of biological and cyber-ecosystems?

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- How can the concept of emotion be defined for self-evolving systems?
- How emotion-based decision making seen in biological ecosystem be simulated in the case of artificial agent working in cyber-ecosystem?
- How can emotional memory and knowledge obtained be stored and retrieved for a self-evolving autonomous agent?

Following are the contributions of this work:

- Analysed the structural similarity between biological and cyber-ecosystems to propose a solution for emotion-based instantaneous decision-making.
- Defined emotion as the manifestation of goals to gain insight into the modelling of artificial emotion.
- Proposed and implemented a novel ontology-based mechanism to represent the relationship between stimuli, emotion and response.
- Proposed a novel method to reason the ontology to elicit appropriate response for the stimuli.
- Applied the proposed method in a cyber security scenario to store and retrieve appropriate response for attack using emotions.

The paper is organised as follows. In section II, we describe the theoretical premises on which we propose our method along with related works in the field of emotion studies and cognitive research. In section III, a cyber attack scenario of DDoS attack is explained as a case study for implementation. In section IV, a mechanism that models the scenario using emotion ontology for emotional decision making is proposed. Section V describes the implementation and section VI concludes the discussion.

II. COMPLEX SYSTEM

In order to understand the nature and dynamics of complex systems, it is imperative to study the vital characteristics of the underlying systems, be it biological, social or cyber security ecosystems. If the structure of these systems are analysed, it is evident that these systems show considerable complexity in their structures. Complexity theory offers intuitive perspective on the underlying structures. Complexity is an emergent behaviour shown as a result of intricate interaction of relatively simpler constituents. Thus, complex systems shows different behaviour or chaotic behaviour compared to its constituent parts. Interdependence in complex systems, which arises from intricate connections existing between components can cause considerable systemic weakness too [3], [4]. Representing the complex systems using complex networks gives effective tools to study the emergent behaviour of these systems [5], [6]. When studying from the perspective of complex networks, it has been revealed that complex networks show similarities in their structure. Barabasi et al. in their seminal paper [7] report a key result about the structure and growth of complex networks in general. It is found that Power law distribution seen commonly in complex networks can be explained by two simple phenomena of growth and preferential attachment. It means that power law degree distribution

can be formed, when network is a growing network and mechanism of growth is in such a way that nodes prefer to form links to those nodes which have higher number of node degrees. This astounding discovery points to another fact that constituent simple elements, which form a complex systems are driven by simple motivations for interactions. Hence, the situation can be stated as follows:

A complex system is formed by the intricate interaction of simple elements driven by simple but fundamental motivations or goals for interactions. This statement is vindicated if we analyse other complex systems like biological networks or global financial networks. For biological networks the fundamental goals are preservation of self and preservation of species. In the case of financial networks, constituent elements are driven by the motivation of maximization of profit. The complexity shown by the network as a whole is the emergent property resulting from goal oriented interaction of the constituent elements. The existence of fundamental goals gives plausible explanation for the existence of complex network.

A. GOAL IN COMPLEX SYSTEM

In order to explain the goal oriented interactions, let us consider the case of human society. It is evident that, as a biological being, humans have fundamental goals such as preservation of self and preservation of species as a whole. However, as an intelligent species, human societal structure and interactions are extremely complex. It seems that individual human beings are motivated by different goals, which are influenced by socio-economical and cultural factors [8], [9]. The analysis is extremely complex and is explored by various philosophers, thinkers and social scientists throughout human history. If it is analysed from the bottom up manner, all other goals can be seen to be originated or influenced by two fundamental goals. If we consider fundamental goals as low level goals, we can see that all high level goals form a hierarchical relationship with low level goals. In other words, fundamental goals are manifested as high level goals. For example, motivation for maximisation of profit arises from the fundamental tendency of accumulation of resources for survival, which can be due to the goal of preservation of self [10]. Likewise, there is a possibility that other goals can also be translated to fundamental goals. In this paper, we try to explore the relationship between the phenomenon of emotion and goals. We also try to analyse emotional decision making from these theoretical aspects.

B. EMOTION AND MODELS OF COGNITION

Efforts to incorporate emotion into artificial intelligence has always been a fascinating field of exploration. Minsky in his famous book emotion machine [11] envision the possibility of exploring artificial emotion through analysing the bond between human cognition and emotions. He discusses the themes of love, pain, consciousness and commonsense. Minsky famously states that “The question is not whether intelligent machines can have any emotions, but whether

machines can be intelligent without any emotions” [12]. The role of emotion in decision making is also emphasised in various ongoing research in cognition studies. Laure et al. [13] describe various efforts to incorporate emotion into the model of cognition. Different definitions of emotions are mentioned such as appraisal theories that combine situational factors with personal significance for evaluation, core affect theory which focuses on appraisal, somatic markers in which declarative memory is attached with emotional markers and primary process affect theory, which is about the emergence of emotion from the perspective of neuro-physiological structures. Sellers [14] proposes a model for emotions for biological and artificial agents. The model defines emotion in a valence and arousal space and incorporates Maslow’s hierarchy for goal satisfaction. The theory emphasises on the motivational and emotional states of the agent and their effect on agent’s social interaction among agents. Coan [15] compares latent and emerging variable models for nature of emotions and supports emerging model, which argues that emotions are caused by their indicators, on the ground of evidences provided by affective neuroscience. Marsella et al. [16] explore the impact of emotion on behaviour and belief. They discuss the coping process of emotion in a virtual reality training environment. Martinez et al. [17] review the studies on human and artificial intelligence. They discuss about various models of emotions such as affective computing, affective agents, Cathexis model, Fuzzy Logic Adaptive Model of Emotions (FLAME), Virtual actors and PECS (Physics, Emotion, Cognition, Social Status) agent architecture. Ptaszynski et al. [18] discuss about estimating affective states of the human computer interaction. They argue that instead of plainly dividing emotions into positive and negative emotions, emotions should be considered as a context sensitive engagement with the world. Greenaway et al. in [19] discuss the interplay between goal, experience and expression of emotions. They explore how awareness of goals restricts or encourage correct expression of emotions. Connemero [20], [21] advocates a bottom up approach in designing emotional system for action selection in autonomous agent. It is argued that the design should be guided by the concern of why the agent needs emotion and it is not desirable to add more emotion than required by the complex agent-environment. In the work of Samsonovich [22], [23], the general framework of emotional Biologically Inspired Cognitive Architecture (eBICA) is extended. The improved architecture includes fluents describing apart from appraisals, somatic markers, emotions, moods, feelings, biases and emotional reactions. Moral schemas and semantic map are the key building blocks for integration. An effort to arrive at a standard model of mind is described in the work of Laird et al. [24], where three cognitive architectures of ACT-R, Soar and Sigma are chosen for the synthesis to form a standard model. Salmeron et al. [25] propose an approach to detect synthetic emotions based on Thayer’s emotional model and Fuzzy Cognitive Maps. They have shown a Fuzzy Cognitive Grey Maps (FGCM) based system for synthetic emotions and prove the possibility to

simulate emotions from raw data obtained from sensors. Cichocki et al. [26] discuss on new generation of Artificial General Intelligence (AGI) systems which relates to complex facets of human intelligence using the concept of multiple intelligence. They have categorized and defined various AGIs depending on their cognitive skills. Thus, numerous models are researched and proposed in the field of cognitive and emotion research. In this work, we focus on the fundamental question of the purpose of emotion in an evolutionary perspective, and how the fundamental goals of human existence manifest through emotions.

C. EMOTIONAL DECISION MAKING

Decision making by an autonomous agent is essentially algorithmic decision making. Explanation of how an algorithm reach a specific decision is important in analysing the decision making process of autonomous agent. Studies in Explainable Artificial Intelligence (XAI) is an evolving field which gives insight into the decision taking process of autonomous agents [27]. The factors affecting algorithmic decisions and bias introduced by algorithms are also relevant in this regard. Shin et al. [28], [29], [30] analyses the cultural impact on the algorithmic learning from users perspective. They further analyse how users involve with over-the-top (OTT) platforms, what awareness the user has of the algorithmic platform and how awareness of algorithmic literacy may impact their interaction with these systems. The question of how emotion positively or negatively affect the decision making process is also widely discussed in the literature. The important research questions addressed in the literature are about the relationship between cognition and emotion, intuition and emotion, and the neural basis of emotion. The studies emphasise the importance of emotion in taking decision in risky situation in a speedy manner. The main discussion point in this context is whether emotional reactions stem from cognitive calculations or whether emotions can guide the decision independently [31]. Quartz [32] suggests the possibility that the basic parameters of financial decision theory is encoded in emotional processes. Thus, the investigations of the neural basis of uncertain choices are suggesting that there are fundamental connections existing between value, motivation and emotions. Sayegh et al. [33] argue that in the rational analysis, emotion acts as a component in rational decisions. Emotion is a key element in the utilisation of tacit knowledge and intuitive decision making strategies. Intuition is widely seen as a vital component in organisational decision making process. Simon [34] explores the role of intuition in judgemental decision making. Zeelenberg et al. [35] also argue that emotions can be understood as programs for decision making using intuition. Their approach named ‘feeling-is-for-doing’ approach recognises the differential impact of emotion arises because of the interplay between emotion and motivation. Sicora et al. [36] discuss the relationship between intuition and emotion and put forward a theoretical frame work to put intuition in social work decision making. Oktar et al. [37] propose that intuition might be prescribed for some decisions

because intuitive decisions are seen as more authentic decisions. Their study based on authenticity of the decision emphasises the importance of intuitive decision in situations where authenticity is plausibly valued. Regarding the interplay between cognition and emotion, though cognition is seen as a rational process unlike emotion, the relationship between cognition and emotion are explored in literature. Toda [38] proposes a model of emotion, based on the assumptions that the emotion forms a system as a result of evolution and is genetically programmed, which helps in taking decisions in primitive and wild environment whereas analytical decision system is evolved later to supplement but not to replace emotional system. This assumption opens the possibility of studying emotional decision making as a purposeful and rational system in its own right. Luo et al. [39] study on behavioral economics and neuroeconomics to provide a model named 'The interactive influence model of emotion and cognition' to elaborate the relationship of emotion and reason in decision making. Lerner et al. [40] also propose the emotion-imbued choice model which takes input from both rational choice theory and emotion research. Schwarz et al. [41] discuss on the multiple link existing between emotion, cognition and decision making based on the influence of moods and emotion experienced at the time of decision making. Zheng et al. [42] summarize the influence of integral emotion and incidental emotion on fairness related decision making. Several other studies [40], [43], [44], [45], [46], [47] also support the observation that emotion aids in decision making. The neural basis for emotion is also investigated in the literature [48], [49]. Rolls [50], [51], [52] put forward two levels of explanation on emotion and decision making. In 'proximate' or mechanical level of explanation, emotion is explained in terms of brain mechanisms. The second level is 'ultimate' level of explanation which focus on the level of adaptive value in evolution. This explanation view emotion as a simple yet efficient way for the genes of the organisms to influence behaviour for their reproductive success. Rewarding and punishing goals for instrumental actions are specified. The resulting states are specified as emotions which indicates achievement or non-achievement of the rewarding or punishing states. This definition of emotional states can be interpreted as the goal oriented definition in the sense that genes are acting according to the fundamental goals of existence. Emotion associated with a person or similar incident creates a bias and a decision is easily reached whether to consider it as positive or negative. This phenomenon is crucial for survival from an evolutionary point of view. When faced with fight or flight situation, the ability to take quick decision is a matter of life and death. It is made possible by assigning emotion to all the previous memories. A new situation is compared with the emotional state of a similar situation and an appropriate decision is taken. If this mechanism was not there, a decision would have needed the energy expensive processing of huge data, which would not be a good survival strategy. Hence, emotions play a critical role in the survival of species.

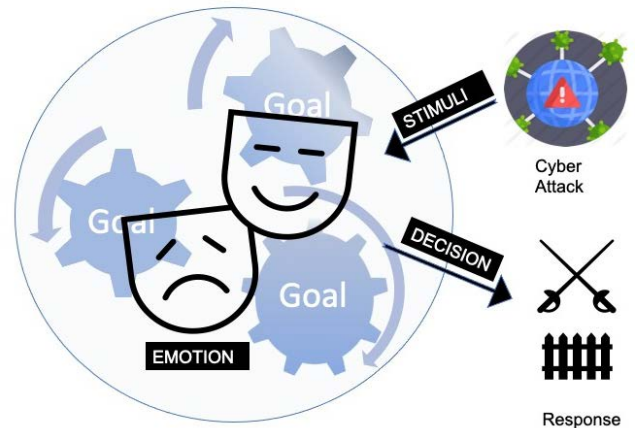


FIGURE 1. Visualisation of emotional decision-making.

D. EMOTION AS THE MANIFESTATION OF GOALS

The above argument provides a new tool to define emotions. As discussed above, constituent parts of complex systems interact with each other driven by simple goals. Biological world is a complex system as its species are driven by simple goals. Hence, all the decisions made by the entities are for the satisfaction of goals. When analysing how satisfaction of goals are perceived, emotions are seen to play a role. Emotions are the manifestation of goals. It is evident that emotions exist in a broad spectrum of positive and negative emotions. Positive emotions are the measure of satisfaction of goals and negative emotions are the measure of how detrimental is the situation to satisfy the goals. As we can see, goals come with varying importance. The manifestation of the goal satisfaction gives rise to valence and its effect is widely studied in emotion studies. However, the emotion models fell short of explaining the reason for existence of emotion in a convincing manner and answering the question of why a particular emotion is felt in a situation.

Figure 1 shows the visualisation of above discussed ideas in the context of cyber security. The relationships between goals, emotions, stimuli and decision are shown in the Figure 1. Attack produces stimuli, which in turn produces emotions that are the manifestation of goals. Emotion produces a decision on the potential responses, which can be broadly categorised as attacking or defensive responses.

III. CASE STUDY

The case study undertaken in this work which is described in [53] can be used as an example scenario to explain the working of the proposed methodology for emotion-based decision-making.

The cyber-attack scenario considered for analysis is DDoS (Distributed Denial of Service) attack. One of the methods used for this attack is TCP SYN flood attack in which premature termination of initiated three way handshake for establishing TCP connection causes the wastage of resources that

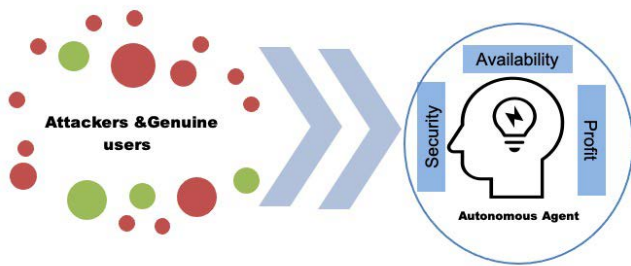


FIGURE 2. Visualisation scenario for case study.

will lead to exhaustion of resource like CPU or bandwidth. Another method which is prevalent due to the growing popularity of IoT devices is HTTP flood attack. In this attack, the attacker exploit seemingly innocuous and legitimate HTTP GET or POST request to attack a web server. HTTP flood attack is usually carried out using botnets, which are the computers taken over by attacker using malware, to simultaneously send large volume of HTTP requests to exhaust the server resources. The fatality in this attack is that the requests used for attack is very much similar to the genuine user requests. Normally, for any e-commerce business that provides service through Internet, getting large volume of user requests shows a good sign of popularity of web site and success of the business model. Besides that, in order to boost the business, e-commerce web sites announce special occasion of sales where they expect large volume of traffic. In these situations, they allocate more resources to manage the increased traffic. Attacker can exploit the situation by artificially creating traffic so that the web site exhausts resources and will be shut down or allocate more resources, which results in financial loss. The scenario is as follows. A server is entrusted by a popular e-commerce website to deliver an important service to the user. The continuous availability of the server is very important to ensure profit for the company. If the server is down or not able to deliver the required service, the brand value of the company will be badly affected. Now, the server faces a situation of sudden surge of user requests. There can be two possible reasons for the sudden surge. It can be due to sudden increase in the popularity of website, which will be highly profitable for the company. It can also be due to a DDoS attack, which will adversely affect the company's reputation.

Figure 2 presents a visualisation for the case study scenario. Attackers and genuine users are requesting for service to the server, which is represented as the autonomous agent.

The autonomous agent under consideration is an intelligent intrusion detection system, which can detect the incoming attack and responds with the appropriate mitigation strategy. The decision taking mechanism of the agent is analysed here. By analysing the scenario, it can be seen that

availability, security and profit can be considered as the goals of the agent. It is assumed that all the actions of the agents are driven by and evaluated against these three goals. The autonomous agent has to preserve availability by ensuring the unobstructed access to the server, enforcing right security access policies and to keep the profit of the company high.

When analysing the case from the perspective of autonomous agents, the essential steps required for taking an action are identification of the type and nature of request, detecting attack if any, recognition of effect of the attack and deciding the appropriate response. Identification of attack type is an intensely researched area in the field of intrusion detection systems. However, since the problem under discussion concerns with identification, storage and retrieval of appropriate response, we assume the knowledge of attack type. In this case, the attack type is DDoS attack. In the following sections, we propose an ontology-based mechanism for storage and retrieval of appropriate response through artificial emotions.

IV. ONTOLOGICAL MECHANISM FOR EMOTION-BASED DECISION-MAKING

Ontology is essentially a semantic structure for storage and retrieval of data [54]. Ontology has already been used to represent in cyber attack scenario [55], [56]. It consists of data properties that are used to model the data associated with a class and object properties for representing how hierarchy of classes form interrelated entities. The ontology proposed here is assumed to act as a growing knowledge base for autonomous agent, which effectively map stimuli and the corresponding response. This knowledge is stored in the knowledge base for future retrieval.

A. ONTOLOGICAL MODELLING OF EMOTIONS

Emotions can be considered as an abstraction of biochemical changes that occur in the body in response to a stimuli. When thinking in terms of theory of evolution, the aim of these biochemical changes is to produce an adequate response to the stimuli so that the goal satisfaction is maximized. For example, a perceived threat to life triggers the biochemical changes that are understood as the emotion 'fear'. The causes of biochemical changes are many, so are the resultant emotions. Though the mapping of biochemical changes to emotions and goal to biochemical changes are complex, it can be inferred that these changes are connected to goals. Hence, it can be assumed that the reason for these biochemical changes are satisfaction of goals and the abstraction of these biochemical changes are the emotions. Hence, for defining emotions, it can be assumed that an emotion can be represented as the cumulative values of biochemical parameters. Here, for modelling the case scenario using ontology, emotion, attack and response to attack are modelled as classes. The classes are defined in the context of a goal-based autonomous agent. The autonomous agent is acting to satisfy the fundamental goals which define the very existence of the agent. Any stimuli received by the agent will have some impact on the goal

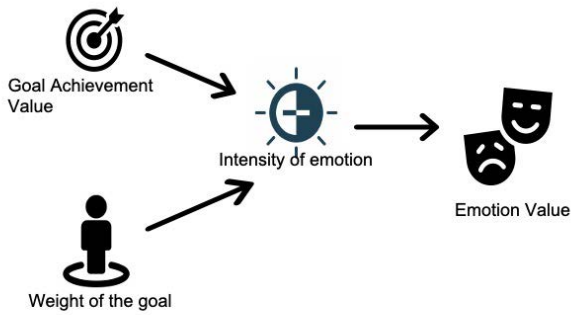


FIGURE 3. Emotion value calculation.

attainment of the agent. Agents select the response according to the emotion evoked by the stimuli. A stimuli can be said to evoke positive emotions if the goal attainment value is high whereas, negative emotions are evoked by low or negative goal attainment value. Hence, in correspondence with the biochemical changes in biological agent, goal attainment value acts as the basis for emotions in artificial autonomous agent.

The three classes that represent stimuli-emotion-response are attack class, emotion class and response class. Attack class represents attacks in a cyber attack scenario. Emotion class is defined as the articulation of goal attainment values. Hence, the data property of the individual emotion is the measure of the goal achievement of individual goals and importance attached to each goal by the agent. The intensity of emotion, which is a value between 0 and 1 gives variance to the feeling of emotion. It helps to model varying manifestation of the same emotion. For example, various intensity of fear can be used to represent infinite variety of similar stimuli. The relationship between goal attainment value, goal weight and intensity is visualised in the Figure 3

The total goal achievement value can be calculated using equation 1

$$GAV_{total} = \sum_{j=1}^n GW_j GAV_j \quad (1)$$

where

- n - Number of goals of the agent
- GW_j - Goal weight assigned to each goal by the agent
- GAV_j - Goal attainment by the given attack for goal j .

A particular range of goal attainment value defines a particular emotion. An individual emotion is also defined by the intensity value. The invokes data property is the expression of these two quantities. The *invokesValue* is calculated using equation 2

$$invokesValue = i \times GAV_{total} \quad (2)$$

where

- i - Intensity of the emotion

The invokes data property of the individual emotion is assigned with *invokesValue*.

The attack class represents the stimuli, which in the case of a cyber attack scenario, are attacks mounted on the cyber

system. For analysis purpose, we consider NSLKDD data set for attack information. In NSLKDD dataset, the attacks are DDoS, probe, U2R and R2L. Our focus is on understanding how the goals of the agent are affected by the attack. This is an assumed value. The quantity *Threat – to – Goal – Value* is defined to articulate the threat posed by an individual attack. *Threat – to – Goal – Value* can be calculated using equation 3

$$TGV_{total} = \sum_{j=1}^n GW_j TGV_j \quad (3)$$

where

- n - Number of goals of the agent
- GW_j - Goal weight assigned to each goal by the agent
- TGV_j - Assumed threat posed to goal j by the given attack

The evokes data property of individual attack represent the assumed threat to the goal of the agent caused by the attack. The threat caused by the attack depends on the *Threat – to – Goal – Value* and the assumed severity of the attack because attacks can cause varying damage based on its severity. The value of severity is assumed as a value between 0 and 1. So, the quantity *evokesValue* is defined to capture the idea of assumed threat and severity, which is calculated using the equation 4

$$evokesValue = s \times TGV_{total} \quad (4)$$

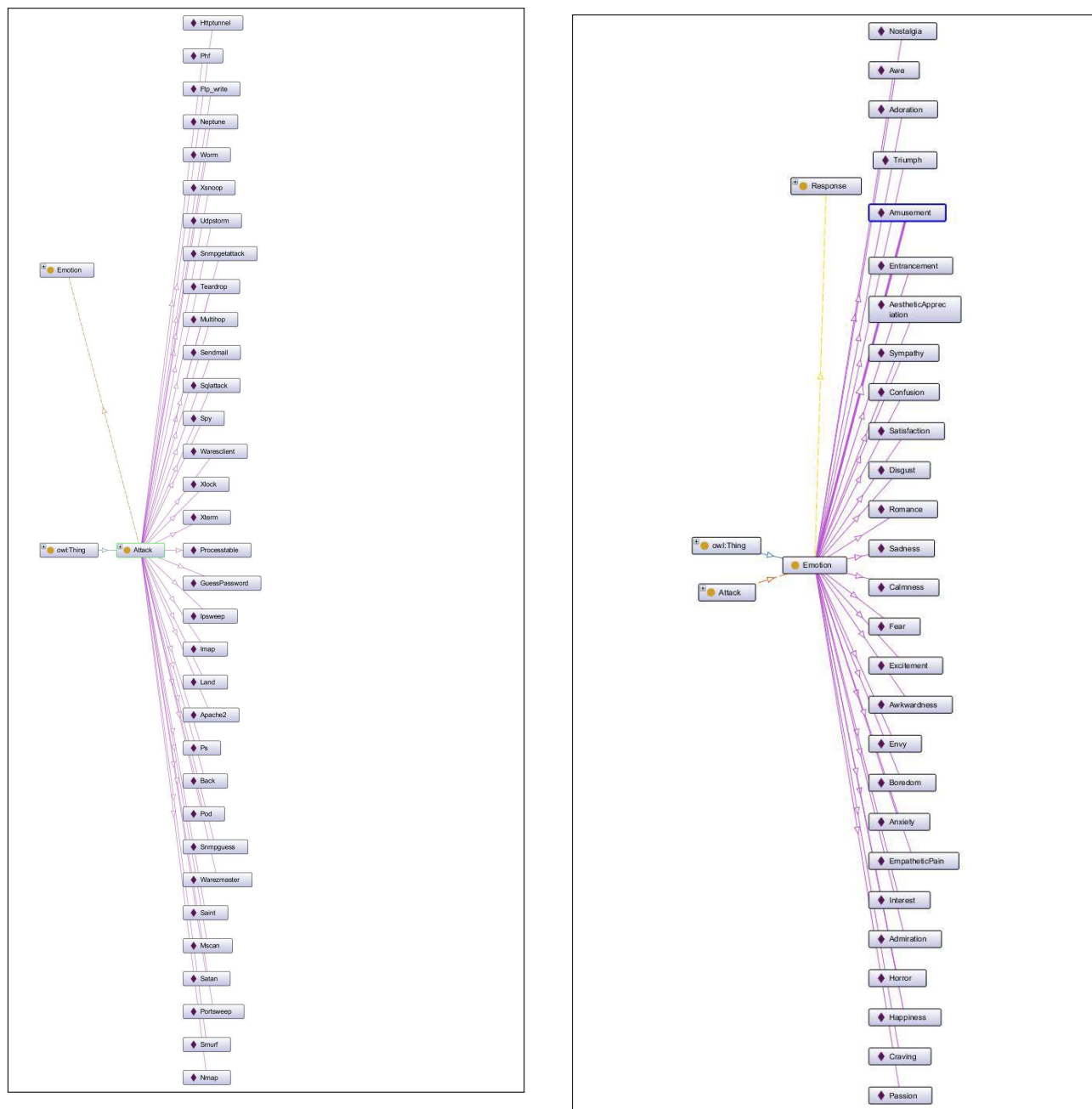
where

- s - Severity of the attack

The evokes data property of the attack class is assigned with *evokesValue*. Response class shows the possible mitigation strategy, the agent can adopt against a particular attack. As mentioned earlier, we assume that the difficult problem of taking a decision on finding an appropriate response strategy for an attack can be expedited by using the emotions. Hence, it is assumed that a response is attached with a particular emotion. It is possible as the intensity of emotion which is a real value between 0 and 1, opens the possibility of defining infinite variance to the same emotion. The connection between individual emotion and individual response is defined using the data property invokedBy of the response class. The value of invokedBy is assigned with the absolute value of *invokesValue* which represents the goal attainment value of emotion. The ‘evokes’ data property which is assigned with *evokesValue* semantically links attack to emotion. Response is invoked by emotion. It is the data property ‘invokes’ that links emotion to response. The equivalence of evokes and invokes values link attack to response through emotion. Figure 4 shows the relationship between data properties of Attack, Emotion and Response classes. This methodology is given in the algorithm 1.

V. IMPLEMENTATION

The ontology and the SPARQL queries for eliciting information from the ontology is constructed using Protege tool [57]. Class diagram is shown in Figure 6. For describing the basic implementation to describe the case study scenario, three



(a) Attack class

(b) Emotion class

(c) Response class

FIGURE 5. Protege implementation of Attack class, Emotion class and Response class.

Algorithm 1 Emotion Ontology Creation and Updation

- 1: **procedure** ontology creation
- 2: Create Attack class
- 3: Create Emotion class
- 4: Create Response class
- 5: Create object property EVOKE to connect Attack class and Emotion class
- 6: Create object property INVOKE to connect Emotion class and Response class
- 7: **procedure** ontology updation
- 8: $n \leftarrow$ number of goals of the agent
- 9: $i \leftarrow$ intensity of the emotion
- 10: $s \leftarrow$ assumed severity of the attack
- 11: $GW_j \leftarrow$ Goal Weight assigned to goal j by the agent
- 12: $GAV_j \leftarrow$ Goal Attainment Value for goal j
- 13: $GAV_{total} \leftarrow$ Total goal attainment value for agent manifested by the individual emotion
- 14: $TGV_j \leftarrow$ Threat-to- Goal-Value for goal j
- 15: $TGV_{total} \leftarrow$ Total Threat – to – Goal – Value for the agent caused by individual attack
- 16: Create individual of Emotion class
- 17: Assign the weight for goal j
- 18: Assign goal attainment value for goal j
- 19: Calculate total goal attainment value of the emotion
- 20: $GAV_{total} = \sum_{j=1}^n GW_j GAV_j$
- 21: Calculate Invokes value of emotion
- 22: $invokesValue = i \times GAV_{total}$
- 23: Assign value of the data property invokes equal to $invokesValue$
- 24: Assign value of the data property evokedBy equal to $invokesValue$
- 25: Create individual of Attack class
- 26: Assign assumed weight for goal j
- 27: Assign assumed Threat – to – Goal – Value for goal j
- 28: Calculate assumed total Threat – to – Goal – Value of the attack
- 29: $TGV_{total} = \sum_{j=1}^n GW_j TGV_j$
- 30: Calculate evokes value of attack
- 31: $evokesValue = s \times TGV_{total}$
- 32: Assign value of the data property evokes equal to $evokesValue$
- 33: Create individual of Response class
- 34: Assign value of the data property invokedBy equal to the absolute value of $invokesValue$
- 35: **procedure** Knowledge retrieval($attack_name$)
- 36: Retrieve $evokesValue$ of the attack using SPARQL query with $attack_name$
- 37: Retrieve Emotion individual with matching $evokedBy$ data property
- 38: Retrieve invokes data property value of the retrieved emotion
- 39: Retrieve matching Response individual using $invokedBy$ data property

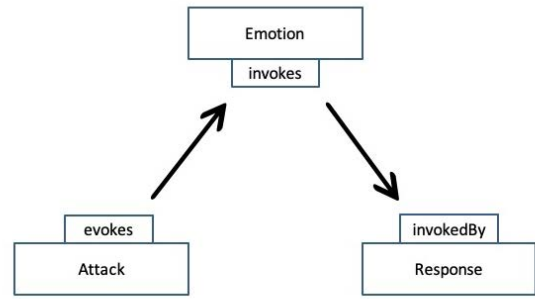


FIGURE 4. Relationship between data properties of Attack, Emotion and Response classes.

TABLE 1. Object properties in Emotion ontology.

Object Property	Domain	Range
EVOKE	Attack	Emotion
INVOKE	Emotion	Response

TABLE 2. Property Assertions of Smurf.

Property	Value
AttackClass	DDoS
threat_to_Profit	-0.5
threat_to_Availability	-0.5
threat_to_Security	-0.5
severity	0.5
evokes	-0.4375

TABLE 3. Property Assertions of Fear.

Data Property	Value
hasProfit	-0.5
evokedBy	-0.4375
invokes	-0.4375
hasAvailability	-0.5
intensity	0.5
hasSecurity	-0.5

TABLE 4. Property Assertions of Terminate_Connection.

Data Property	Value
invokedBy	0.4375

classes of Attack, Emotion and Response are created. Class diagram shows the relationship between the classes.

Attack class is the ontological representation of possible cyber attacks. In order to restrict the discussion to our proposed mechanism, only the relevant subset of attacks that are relevant in the case study is modelled and is shown in Figure 5a.

As already described, the emotion class is described as the manifestation of goals of agent, and is shown in Figure 5b. The 27 individual emotions in the ontology are modelled as given by Cowen et al. [58]. The emotions are determined by the total goal attainment value associated with it. Negative values of goal attainment are associated with negative

TABLE 5. Classes and Individuals of Emotion Ontology.

Class	Individuals
Attack	Httpunnel, phf, Ftp_write, Neptune, Worm, Xsnoop, Udpstorm, SntpgetAttack, Teardrop, Multihop, Sendmail, Sqlattak, Spy, Waresclient, Xlock, Xterm, Processtable, GuessPassword, Ipsweep, Imap, Land, Ps, Back, Pod, Sntpguess, Warezmaster, Saint, Mscan, Satan, Portsweep, Smurf, Nmap
Emotion	Nostalgia, Awe, Adoration, Triumph, Amusement, Entrancement, AestheticAppreciation, Symathy, Confusion, Satisfaction, Disgust, Romance, Sadness, Calmness, Fear, Excitement, Awkwardness, Envy, Boredom, Anxiety, EmpatheticPain, Interest, Admiration, Horror, Happiness, Craving, Passion
Response	Terminate_Connection, Allocate_More_Resources

TABLE 6. SPARQL queries.

Query No.	SPARQL Query	Query Result
1	PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX xsd: <http://www.w3.org/2001/XMLSchema> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema> PREFIX eo: <http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#> SELECT ?Attack ?evokes WHERE ?Attack eo:evokes ?evokes	http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#Smurf 0.4375"lhttp://www.w3.org/2001/XMLSchemadouble>
2	PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX xsd: <http://www.w3.org/2001/XMLSchema> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema> PREFIX eo: <http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#> SELECT ?Emotion WHERE ?Emotion eo:evokedBy -0.4375	http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#Fear
3	PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX xsd: <http://www.w3.org/2001/XMLSchema> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema> PREFIX eo: <http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#> SELECT ?Emotion ?invokes WHERE ?Emotion eo:invokes ?invokes	http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#Fear "-0.4375"lhttp://www.w3.org/2001/XMLSchemadecimal>
4	PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX xsd: <http://www.w3.org/2001/XMLSchema> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema> PREFIX eo: <http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#> SELECT ?Response WHERE ?Response eo:invokedBy 0.4375	http://www.semanticweb.org/admin/ontologies/2019/9/EmotionOntology-Data#Terminate_Connection

emotions and positive values of goal attainment are associated with positive emotions. A predetermined range of values are assumed to correspond to particular emotions. These values are design parameters that can be predetermined according to the case under consideration. Though the uses of various positive and negative emotions can be contemplated in different scenarios, we restrict our discussion to the emotion ‘Fear’ in the current case study.

Response class models possible response to an attack which is shown in Figure 5c. In this discussion, we consider the response of terminating connection in order to mitigate DDoS attack. The classes and individuals defined in the emotion ontology is given in the Table 5. The EVOKE object property connects Attack class and Emotion class through the values of goal attainment. Similarly, the object property INVOKE connects Emotion class and Response class. The object properties of emotion ontology are given in Table 1.

The property assertions are the assertion of goal achievement values of individuals of Attack, Emotion and Response

classes. Individual considered here is Smurf attack, which is a type of DoS attack, emotion Fear and response Terminate Connection as shown in Table 2, Table 3 and Table 4 respectively. Property assertion involves determining goal achievement value for each individual. Values of the data properties such as evokes, evokedBy, invokes and invokedBy are assigned to individuals in line with the value of total goal attainment and assumed threat to goal value of the attack. For example, in the case study under consideration, smurf attack is assumed to cause a negative goal attainment of -0.4375 , which can also be perceived as threat to goal value caused by smurf attack. Fear is a negative emotion whose invokes value is -0.4375 . So it is assumed that smurf attack evokes the emotion fear. The value of invokedBy data property of individual response is stored as absolute value of goal attainment value of the emotion fear. By this, we mean that ‘terminate connection’ is the suitable response obtained for the ‘smurf attack’ through the emotion ‘fear’. The purpose of using ontology is to store these related information of smurf evokes ‘fear’, which in turn invokes the response ‘terminate

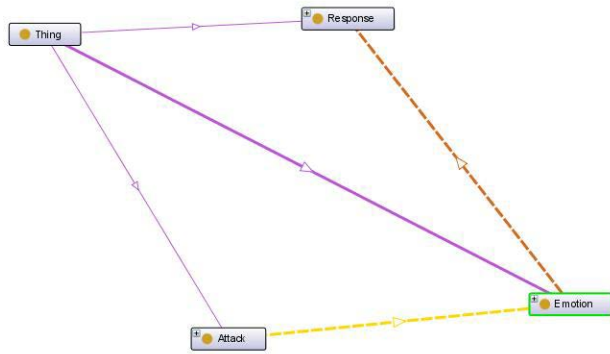


FIGURE 6. Class diagram.

connection'. The model explained here is a fundamental model that can be extended to store more complex information.

VI. ELICITING INFORMATION FROM ONTOLOGY

The emotional ontology described above acts as a knowledge base for the autonomous agent. The ontology connects knowledge about an attack, emotion that should be associated with that attack, and the potential response associated with that emotion. The knowledge about response corresponding to attack can be obtained by reasoning the ontology. SPARQL query is the query language used for ABOX reasoning about individuals. Here, a series of SPARQL queries are used to reason about the connection between attacks, associated emotion and optimal response. Query 1 is used for getting the goal attainment value of the attack using the data property evokes. Query 2 is used for getting emotion associated with the retrieved goal attainment value. Query 3 retrieves response invocation value of the emotion and Query 4 outputs the response associated with the response invocation value. The SPARQL queries and obtained result for the present case study are shown in Table 6.

VII. CONCLUSION AND FUTURE SCOPE

The possibility of modelling artificial emotions for autonomous agents has been explored in the work. Emotion is the basis of taking intuitive decision, which is inevitable for survival in the biological world. Cyber ecosystem, which is similar in structure to biological ecosystem, involves the continuous battle of existence between attackers and defenders. Attackers always get a competitive edge when deploying zero day attacks with novel strategies. In order to counter these strategies, defenders are forced to take instantaneous decisions. Simulating emotion-based decision can be novel but a useful strategy in this scenario. In order to do so, emotion is defined as the manifestation of goals. A novel ontology-based mechanism is used to represent the relation of emotion with stimuli and response. Implementation of the method involving representation of emotions and retrieval of response is explained using case study of a DDoS attack scenario. This

work is done as the part of realising a self-evolving cyber security system which can simulate the evolutionary process of biological ecosystem to meet the challenges of cyber ecosystem. The implementation described in the present work is simple enough to explain the method. In future, it is possible to develop comprehensive ontologies involving already existing cyber security ontologies.

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RENDHIR R. PRASAD received the B.Tech. degree in information technology from the Cochin University of Science and Technology, Kerala, and the M.Tech. degree in information technology from the Indian Institute of Technology, Kharagpur. He is currently pursuing the Ph.D. degree with the Department of Electronics and Communication Engineering, College of Engineering, Trivandrum, affiliated to A. P. J. Abdul Kalam Technological University, Kerala. He is also working as an Assistant Professor with the Department of Information Technology, Government Engineering College Barton Hill, Thiruvananthapuram, Kerala, India. His research interests include self-evolving and self-healing cyber security systems, game theoretical modeling of negotiations in cyber security, and economics of cyber security.



CIZA THOMAS is currently working as a Senior Joint Director and the Directorate of Technical Education Kerala, India. She has published more than 70 international journals and international conference proceedings and more than 50 national conference publications. She has edited nine books in the field of sensor fusion, complex systems, ontology in information science, and data mining. She has published 15 book chapters in the field of network security and pattern recognition. Her research interests include network security with research interest in the fields of information security, data mining, sensor fusion, pattern recognition, information retrieval, digital signal processing, and image processing. She is a reviewer of more than ten reputed international journals, including IEEE TRANSACTIONS ON SIGNAL PROCESSING, IEEE TRANSACTIONS ON NEURAL NETWORKS, *International Journal of Network Security*, *International Journal of Network Management*, and *IEEE-John Wiley International Journal on Security and Communications Network*. She is a Guest Editor of the *IEEE Security & Privacy* magazine.

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