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# Acquisition of Abstract Words for Cognitive Robots

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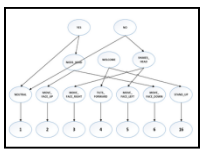
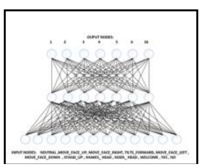




**Abstract**

Abstract word learning and comprehension is a very crucial and important issue because of its application and problematic nature. This problem does not just belong to the cognitive robotics field, as it also has significance in neuroscience and cognitive science. There are many issues like symbol grounding problem and sensory motor processing within grounded cognition framework and conceptual knowledge representation methods that have to be addressed and solved for the acquisition of abstract words in cognitive robots. This paper explains these concepts and matters, and also elucidates how these are linked to this problem. In this paper, first symbol grounding problem is discussed, and after that an overview of grounded cognition be given along with detail of methods/ideas that suggest how abstract word representation could use sensory motor system. Finally, the computation methods used for the representation of conceptual knowledge are discussed. Two cognitive robotics models based on Neural network and Semantic network that ground abstract words are presented and compared via simulation experiment to find out the pros and cons of computation methods for this problem. The aim of this paper is to explore the building blocks of cognitive robotics model at theoretical and experimental level, for grounding of abstract words.

*Keywords*: Abstract words; symbol grounding problem; grounded cognition; knowledge representation; neural network; semantic network



## ■1.0 INTRODUCTION

Cognitive developmental robotics is an innovative approach in the robotics field, and it focuses on the development of cognitive processes in humanoid robots. The embodiment view of cognition, which emphasized on the role of body structure and interaction with the environment [1, 2] has influenced different fields, from neuroscience to robotics. Due to this, the importance of humanoid robots in the scientific research of cognitive science has increased [3].

Achieving human level intelligence is an ultimate goal of the cognitive robotics field. Language is one of the unique qualities of humans. Robots with language comprehension and production quality could be practiced effectively in human–robot interaction tasks.

For development of linguistic ability in robots, cognitive developmental robotics takes inspiration from child language acquisition methods [4]. The children get command on symbol manipulation capabilities like productive language use is based on the establishment of combination of verbal and non-verbal communication routines with their caretakers. Before getting a line of language, children pass through long perceptual exploration phase. After that interaction with preverbal babies and young children are exist in the immediate context. These interactions allow the children to make direct link between the perception of objects, events and linguistic utterance [5]. Later on, situationally detached information is presented to children [6]. The words that are learned in immediate context or that has perceptual link with symbol are called concrete words. It means concrete word's semantic referent could be perceived through the senses. The words that are just learning through language are called abstract word. Until recently, most of the research in cognitive systems focused on acquisition of concrete words. The acquisition of concrete words also has been achieved successfully in robots [7, 8], but there is little is known about representation of abstract words. According to general definition, abstract words links to entities that are not physically exist, nor spatially constrained [9]. These words could not be comprehended through the senses but by the mind [10]. The concepts behind these words could not be directly linked with perceptions and sensorimotor experience because these are intangible and direct interaction with them is not possible.

Due to the lack of physical referents of these words/concept, the development of a cognitive model that can learn the meaning of abstract wordsis a very importantmatter in cognitive robots, and also in cognitive science and neuroscience.

To design a cognitive robotics model for the acquisition of abstract words, there are many issues that have to consider, understood, and solved. For example, role of grounded cognition in language models which is one of the most influential hypothesis of cognition. Another problem which ispertinent withsymbol manipulation system like symbol grounding problem also has to address and solved. For implementation of abstract words acquisition model with above mentioned considerations, importantly, it matters how the conceptual knowledge of the robot will be represented. This means we need to know which knowledge representation method should be employed for modelling of conceptual system that process abstract words.

By taking in view the importance of this problem, this paper explains grounded cognition hypothesis, symbol grounding problem and conceptual knowledge representation methods and identifies how these are related to this problem. The objective of this paper is to explore the concerns and building blocks of a cognitive robotics model for the acquisition of abstract words.

The paper describes about the symbol grounding problem in Section 2, and then details of the grounded cognition view and the ideas /methods of grounding abstract words in a sensory motor representation are given in Section 3. In Section 4, conceptual knowledge representation methods for cognitive systems are discussed. Subsequently, in this section two cognitive robotics model are presented, and [11-16] experimented and theoretically compared to present weaknesses and potentials of knowledge representation methods for abstract word processing system. The paper ends with a discussion and concluding remarks in Section 5.

## 2.0 SYMBOL GROUNDING PROBLEM

In language processing system or cognitive model the process by which meaning is attached with symbol or symbol linked with semantic representation of the world is a very important issue for the field of cognitive science, artificial intelligence, philosophy, semiotic, and as well as for cognitive robotics. Because of its importance, in the last decade, there has been seen tremendous increase in models of language acquisition and evolution of communication in the field of robotics. These models keep in view this problem and attach meaning to symbol through direct interaction of robot agent forthe real world.

This problem is devised by Harnad [17], and it is related to matter how symbols get meanings or how referents of symbols are acquired in symbol processing system. A symbol processing system, like a computer program manipulates meaningless symbols in a way that is systematically interpreted as meaning (e.g. Chess move and payroll system). Although the symbol in this arrangement bears a meaning which depends upon user interpretation, symbols and system are subject to a symbol grounding problem. According to this view, a symbol system should ultimately meet with representations that were acquired through direct interactions with the environment [18].

Obviously, this necessity of the symbol manipulation system could be fitted on concrete word. Because concrete words has a perceptual experience that take place from the external environmental interactions. How abstract words could go in this type of model that regards the symbol grounding problem? The explicit definition of a symbol that is given by Harnad in [17] clear this point. According to Harnad, symbol required logical link and these logical links which are actually symbol-symbol links support the productivity and generatively in language. This also contributes to grounding of abstract words and symbols. It means that if a cognitive agent acquire symbol meaning through direct interaction, then remaining symbols could get the meaning through the logical combination of symbols, which is case of abstract word. For abstract word processing model, symbol grounding problem has to address and solved through attachment of symbol-symbol logical link to external environmental interactions.

## 3.0 GROUNDED COGNITION AND SENSORY MOTOR PROCESSING

One of the prominent ideas at the core of recent cognition theories is that elements of thought are visual, and motor images [1, 2, 19, 20] and this is commonly labelled as grounded cognition. According to this hypothesis, thinking is based on the activation of a sensory motor system. This view says that when a person thinks about anything (like apple), neural patterns that were formed previously during interaction with this thing are activated. This reactivation of neural patterns results in sensory-motor simulation. Grounded cognition has solved the issue of the symbol grounding problem. Because sensory motor simulations could provide grounding to symbols.

Most of the evidences that support grounded cognition framework focused on concrete words representations [21] or actions [22]. At first glimpse, the adaptation of this framework for the processing of abstract word looks illogical because abstract words like peace and democracy do not have any particular shape, colour, weight, sound, or smell. These words are associated with other words like freedom and majority etc. On the other hand, there is a lot of theoretical and empirical evidence for the involvement of sensorimotor and embodiment roles in language use [23, 24]. Embodiment view of cognition states that both concrete and abstract words are grounded in perception and action, and because of this both are model [25].

For the development of linguistic ability in cognitive agents with grounded and embodiment view different approaches have been adopted. In these models, external environment plays an important role for language. Therefore, language is grounded in sensorimotor and cognitive knowledge of cognitive agents [4, 26] . Some of these models focus on the emergence of a shared lexicon through cultural and biological evolution [27]. In these models, a population of cognitive agents initialized with random language are capable of constructing sensory-motor representations during interaction with surroundings. Due to the iterative process of communication and game they converge towards a shared lexicon. There are many models that have been proposed for the acquisition of language and concrete words, but few of them deal with abstract words.

The adaptation of a grounded cognition view for abstract word processing in a cognitive robotics model will make it immune to the symbol grounding problem because by using the sensory motor system the semantic referents of abstract words will be motor and image elements not just verbal symbols like in ungrounded models and dictionaries structures.

### 3.1 Sensory Motor Representation for Abstract Words

For the acquisition of abstract words in a grounded cognition framework (which is a good candidate to deal with symbol grounding problems), the question which arises is how a sensory motor system could be used for abstract word representations. In the following section, two methods are presented for the solution of this matter. These methods are based on situation and metaphor theories.

#### *3.1.1 Abstract Words Representations by Situations*

Barsalou and Wiemer-Hastings [9] proposed that specific situations in which abstract words occur and introspective experience might be simulated in response to abstract concepts. The role of situations is also suggested by context availability models of Schwanenflugel and Shoben [28, 29]. They argue that in order to understand a word and sentence people have to represent the context in which the word or sentence has meaning. They also argued for the difference in abstract words and concrete words, and opined that the difficulty of an appropriate context finding for abstract words is the base of the difference between abstract words and concrete words. According to Barsalou and Wiemer-Hastings [9], abstract concepts are used in a wide variety of contexts, and specific event for abstract words are more complex than concrete concepts. Representation of abstract words might be formed by the sum of concrete situations that share the abstract word. This mechanism has been used in exemplar models [30]. In exemplar models, experiences store exemplar and cue activates, and different exemplar and abstract words are achieved from these exemplars in a summary form. In the same way, representations of concrete situations could allow the grounding of the abstract concept in sensory motor simulations. As a conclusion of these views, abstract words might be grounded in sensory motor simulations in an indirect way.

#### *3.1.2 Metaphor Theory*

One of the very different ideas that were originated in cognitive linguistics is based on metaphorically grounding abstract words in concrete situations [31, 32]. As people understand the problem solving method by moving from initial point (situation) to end point (solution). In the same way, this view suggests that abstract concepts are understood by an analogy between the representations of concrete words. For example, the word ANGER is grounded in the concrete situation, like boiling water exploding out of the pot. However, direct experience of abstract concepts is central to their contents [9]. For example, for ANGER people have experienced with thesituations that trigger anger, and they know how people look and act when they are angry.

When we apply this theory on Barsalou and Wiemer-Hastings theory [9], then concrete concepts served as a metaphor/vehicle to represent abstract words. Lakoff and Johnson [31] used the term conceptual mapping or conceptual metaphors, and the basic claim of this theory is that concrete vehicles partially structure abstract words, and the full representation of the vehicle is necessary in order to fully identify abstract words [33, 34] . Conceptual metaphor theory can explain how the representation of abstract words could use a sensory motor system due to the thoughtfulness of the vehicle as concrete physical experience.

## ■4.0 REPRESENATION METHODS FOR CONCEPTUAL KNOWLEDGE

Concepts have central role in information processing because they are the basis for language, object recognition, and action planning, and they constitute the meaning of events, objects, and abstract ideas [35, 36] . One of the significant elements of designing a cognitive model is how the conceptual knowledge will be represented internally.Basically, there are two paradigms to computationally represent the knowledge for any cognitive system. One is called symbolic, and the other one is called the sub-symbolic/connectionists representation method.

The symbolic paradigm is earliest conceptual representation method, and for many decades the influential theories of concept processing were based on this method [37-39]. In this paradigm, each concept is represented by a node, and these nodes are linked to the other nodes and this makes the meaning of the full structure. This structure of connected nodes is called a semantic network. These structures provide meaningful prepositional knowledge.

Because ofthe deficiency of conceptual flexibility in classic semantic network, this paradigm appeared unsatisfactory for some researchers. For that reason connectionist or sub-symbolic models were developed [40, 41]. In Connectionist/Sub-symbolic representation method, the concept is formed by different simple representation units or this formalism is based on parallel distributed processing. The concepts are recovered through propagation of activation between processing units, which are connected in a network. These networks are called artificial neural networks.

Both of these formalisms have been used for concept representation in roboticsand cognitive agents models [42-45]. These methods have some processing constraints and design attributes that influence the models of conceptual knowledge. However, each one has its own merits and demerits, and is not adequate for all problems.

Two cognitive robotics model are presented in the next section to demonstrate and compare strengths and weaknesses of symbolic and connectionist approach for this problem.

### 4.1 Models Detail

Both of the cognitive robotics models (based on Symbolic and sub-symbolic paradigms) which are presented in this paper indirectly ground abstract words in sensorimotor representation by using the combinatorial language property. One of the model is based on semantic network and second model is based on feed forward neural network. These models have used the abstract word category which belongs to the motions of robots and find the semantic referent of abstract words in term of primitives, which are assumed as acquired through sensorimotor interactions. Actions which are available in motion manager part of the software library of DARwIn-OP robot simulator are considered as semantic primitives.

These models are implemented in software environment. Semantic network model is implemented by using Java programming language. Neural network model is simulated through neural network software from AIspace* system repository. This software also programmed in java language. It is available at www.AIspace.org. This system provides several arificial intelligence software tools.

**Table 1** Data for models

| Abstract words | |
|---|---|
| SHAKES_ HEAD, NODS_ HEAD, WELCOME, YES, NO | |
| **Semantic referents (Symbolic names → Motion files)** | |
| 1. NEUTRAL→1<br>2. MOVE_FACE_UP→2<br>3. MOVE_FACE_RIGHT→3<br>4. TILTS_FORWARD→4 | 5. MOVE_FACE_LEFT→5<br>6. MOVE_FACE_DOWN→6<br>7. STAND_UP→16 |

For both simulation experiments that are going to be presented, the list of abstract words and semantic primitives with their symbolic names is shown in Table 1. Motion files has numerical names in DARwIn-OP robot simulator, therefore symbolic names are given to these motion files.

#### *4.1.1 DARwIn-OP Robot and Simulation Model*

The DARwIn-OP is an open source humanoid robotic platform developed by ROBOTIS (a Korean robot manufacturer) in affiliation with the University of Pennsylvania. The DARwIn-OP stands for Dynamic Anthropomorphic Robot with Intelligence-Open Platform. It is mainly used for educational and research purpose in universities and research centers [46]. It has 20 degrees of freedoms allocated as follows: 3 in each arm, 6 in each leg, 2 in the head.

**Figure 1a** DARwIn-OP robot

**Figure 1b** Simulation model

The DARwIn-OP robot and its simulation model is shown in Figures 1a and 1b. The simulation model has been designed to be as close as possible to the real robot. It has different sensors and actuators: 20 servos, 5 LEDS, one camera, a three axes accelerometer, a three axes accelerometer, a three axes gyroscope.

Simulations of cognitive robotics model, which are presented in this paper used actions primitive which are available in motion manager part of a software library of DARwIn-OP robot simulator. Apart from predefined motions, which are available in this software repository, new motions also could be developed using the action editor tool in this simulator.

### *4.1.2 Semantic Network Model*

This model belongs to symbolic approach, the core of this model is a semantic network of N concept nodes, each represents one concept (For instance, concrete or abstract).The semantic network which is presented is a digraph structure with associative link,i.e,

$$G = (V, E) \qquad (1)$$

Here $V$ represents $N$ concepts and $E$ represent the association between $N$ concepts. $E$ for each concept shows the semantic relatedness concepts list.

The methodology which is adopted here for acquisition of abstract words consist of two phases: learning and recalling.As abstract word are learned through language[47], in learning phase the linguistic input is provided in the form of text input, which is consist of user description of abstract word like SHAKES_ HEAD is MOVE_FACE_RIGHT and MOVE_FACE_LEFT. This input is internally stored as a semantic network or mapped into an internal representation. After that remaining words are mapped into an internal representation (semantic network) by considering user description shown in Table 2. Semantic network for this model is presented in Figure 2.

**Table 2** Description of abstract words

| Abstract words | User Description |
|---|---|
| SHAKES_ HEAD | SHAKES_ HEAD is MOVE_FACE_RIGHT and MOVE_FACE_LEFT |
| NODS_ HEAD | NODS_ HEAD is MOVE_FACE_UP and MOVE_FACE_DOWN |
| WELCOME | WELCOME is STANDUP and TILTS_FORWARD |
| YES | YES is NEUTRAL and NODS_ HEAD |
| NO | NO is NEUTRAL and SHAKES _ HEAD |

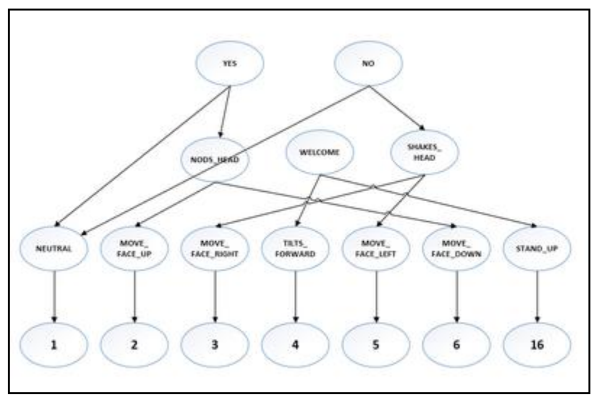
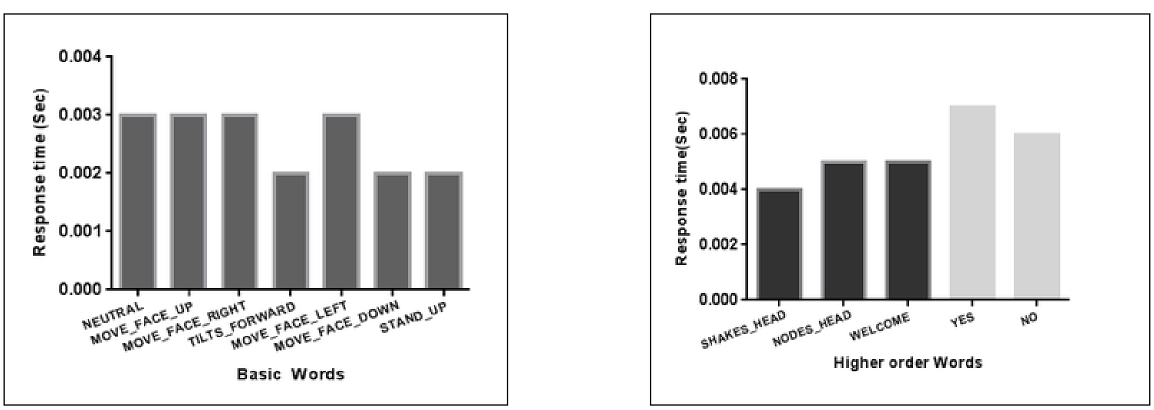



**Figure 2** Semantic network model




(a) (b)

**Figure 3** Response time of symbolic name (a), Response time of abstract word

In recalling phase, transitive inference method is used to find semantic referents of abstract words. Transitivity based inference has been shown and explained in humans [48, 49] and also in animals [50]. This property also has been used in robotic models between different relation[51, 52]. Transitive property which is used in this model for inference is defined as

$$\forall a, b, c \in X : \{aRb \wedge bRc\} \Rightarrow aRc \quad (2)$$

Here X is set of nodes of semantic network.

This property is applied on recalled node and response/output is generated in term of semantic primitive nodes through searching and mapping. For example when YES is called then robot first search direct precedent of YES means NEUTRAL and NODS_ HEAD, in same way NEUTRAL and NODS_ HEAD is replaced by 1,2 and 6. These are primitive nodes and response is generated in terms 1,2 and 6 primitives.

### Simulation Results

As described in the previous section, after the organization of robot conceptual knowledge, the learned words are recalled. In end of simulation all abstract words were learned which verified through recalling of abstract words. The response time of recalled words are shown in Figure 3a and Figure 3b. It is obvious from respons time graphs that it is linear O(V+E).Words recalling in this model depens upon number semantic related words.

### 4.1.3 Neural Network Model

The Second model which is presented here is an example of the Sub-Symbolic approach. It consists of a Feed Forward Neural Network. It is fully connected feed forward neural network.It has 12 input nodes, 7 hidden nodes and 7 output nodes which is shown in Figure 4.

The sigmoid function is used for hidden and output layers as activation function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (3)$$

The neural network is trained using standard back propagation algorithm [40].

To ground abstract words, simulation experiment takes inspiration from Cangelosi [7]. Simulation experiment consists of three steps: namely

- Basic Grounding (BG)
- Higher order grounding (HG1)
- Higher order grounding (HG2)

In BG stage, The 7 motion files (1,2,3,4,5,6,16) are associated with their symbolic names. This is called direct grounding stage.

During this stage, the output is computed by applying back propagation algorithm and weight correction are adjusted.

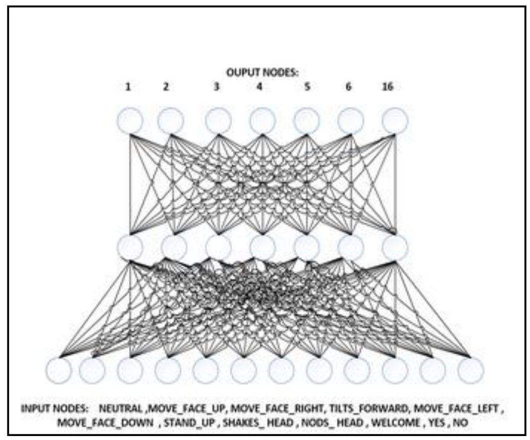



**Figure 4** Architecture of feed forward neural network

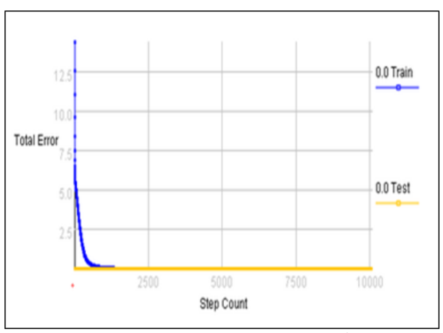



**Figure 5a** Root Mean Square Error of BG stage

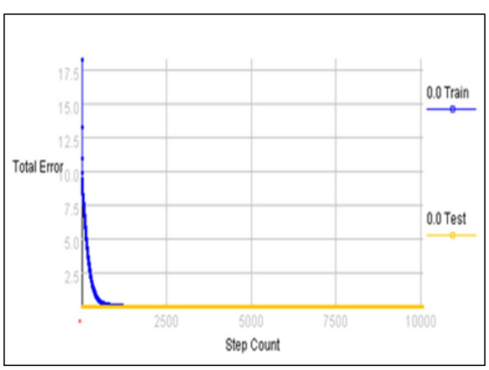



**Figure 5b** Root Mean Square Error of HG1 stage

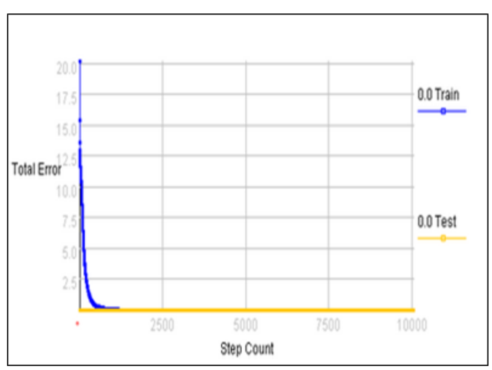



**Figure 5c** Root Mean Square Error of HG3 stage

In HG1 and HG2 stages, the abstract words are learned byapplying the following procedure. Firstly the words that are described in linguistic description like WELCOME is STANDUP and TILTS_FORWARD, here STAND_UP and TILTS_FORWARD (descriptive words) of abstract word (WELCOME) are inputted to network one by one and the response of these words is linked with abstract words WELCOME through training. For example, when STANDUP and TILTS_FORWARD are inputted to network, then 16, 4 neurons become active then this output is linked with an abstract word WELCOME through back propagation algorithm. For detail of this procedure see paper [53]. All of the other abstract words SHAKES_ HEAD, NODS_ HEAD, YES, NO learnt through the same procedure by using the user description of words given in Table 2.

**Table 3** Simulation Parameters

| Training Stage | No. of Iterations | Larn Rate | RMSE |
|---|---|---|---|
| **BG** | **10000** | **0.2** | **0.0067** |
| **HG1** | **10000** | **0.2** | **0.0078** |
| **HG2** | **10000** | **0.2** | **0.0089** |

### *Simulation Results*

As described in the above section that training mechanism of the neural network consists of three incremental stages. Figures 5a, 5b and 5c show the root means square error for each stage. Detail of the simulation parameters that were used for training of neural network is shown in Table 3.

At the end of training of the neural network, all of the words were successfully learned.Simulation results show that neural network training has taken same no of iterations and other parameter for all stages.

## 4.2 Comparison of Semantic Network and Neural Network

In subsequent sections, Semantic network and neural network are compared through simulation results and as well as in the theoretical manner.

### *4.2.1 Simulation Results Comparison*

To analyze the results of both models of abstract word processing, the hamming distance method is applied to output response of models and the results are graphically presented.

The hamming distance between two strings $x = (x1, x2,..., xn)$ and $y = (y1, y2,..., yn)$ is defined as

$$d_H(x, y) := \#\{ j : x_j \neq y_j \} \tag{4}$$

The hamming distance between the target output string and output string is calculated for each already learned abstract word.

The deviation graph for the humming distance of semantic network and neural responses with targeted output is shown in Figure 6. It is clear from graph that neural network doesn't have the same output sequence as required sequence for WELCOME abstract word because it cannot differentiate between sequences of output event, therefore it subject to combinatorial ambiguity. Semantic network hamming distance for each word is zero. It delivers an accurate output string.

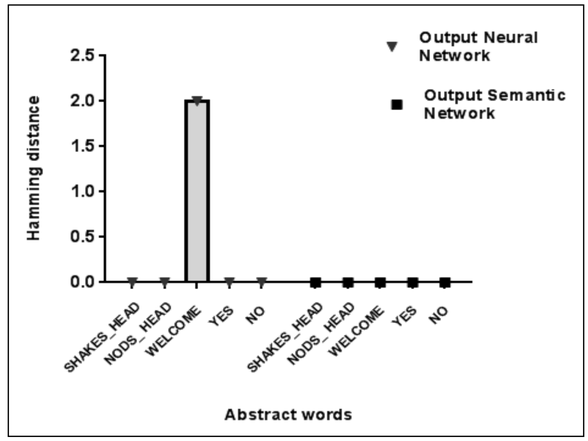



**Figure 6** Hamming Distance of abstract words output responses

### *4.2.2 Theoretical Comparison*

Besides of the above described property there are other attributes of these networks that should be considered for cognitive robotics model for abstract word processing. Like one of the most important ones is storage capacity.

The neural network has generalization nature [53]. After a particular point the learning error again increase that's why it has limited capacity and ultimately it cannot recall all input accurately. Semantic network has a high storage capacity and accuracy [54].

The next important point that has to consider is that neural network is immuned to symbol grounding problem because in neural network symbol could be attached with their perception. The neural network model, which is presented here does not subject to the symbol grounding problem. The main weakness of the symbolic method is that it cannot attach perception with a symbol, and in a symbolic system concept is represented merely by a single node, and these systems are subject to the symbol grounding problem. However, these systems could handle this problem by using some strategy like as solved in above presented model some nodes that were linked with sensorimotor representations.

Both of these models have their own design weaknesses and strength like in the semantic network if observed keenly than there is no semantic, it is an algorithm that gives meaning to symbols and mostly this approach is thought that less degree of freedom in behavior. But semantic network is more flexible and high degree of freedom in behavior. Another attribute which is related to these models is called compositional structure. Connectionist models do not give details about the compositional structure as shown in Figure 4. On the other hand semantic network shows detail of structure, it is observable from Figure 2.

## ■5.0 DISCUSSION AND CONCLUSION

Having the capability of understanding abstract words is very important for linguistic ability of the robot. According to [17], if the design of linguistic agent allows the grounding of words just through direct interactions then it is not enough. One of the most important characteristic of human language is productivity through which new concept can be expressed by combination of words. If robot has ability of understanding abstract words then ultimately it would be able to extend its basic knowledge since abstract word acquisition is based on a combinational language factor. The structure and content of abstract words/concepts have been investigated to much lesser exten than concrete concepts and that's why there is little consensus about conceptual system that process abstract words. Acquisition of abstract words in cognitive robots is a problematic issue because of debate on nature of these concepts and other important factors.

In this paper, indepth view of the concerns and issues that has to be address and solved by abstract word processing system is given. These concept pose classic problem for symbol grounding hypothesis and for grounded cognition theories. Symbol grounding hypothesis put requirement on symbol processing system that symbol referent should come in to system through environment interactions. For language grounding model of abstract words, the problem of symbol grounding has to be solved because these words do not have perception. Abstract words could be ground through logical linking of symbols to external evironment representastions. Grounded cognition hypothesis emphasize that main referent of symbol are not just symbol but are sensorimotor and perceptual elements. It means conceptual system in thinking process activates sensory motor brain areas [55]. By considering grounded cognition view, abstract words processing system could be immune from symbol grounding problem.

There are different theories that suggest how abstract words can use sensory motor representations. One of them, Barsalou and Wiemer-Hastings [9] suggests a specific situation in which abstract words occur and introspective experience might be simulated in response to abstract concepts. The second pointed out that the abstract words could be grounded in a concrete situation metaphorically [32].

In addition to these considerations, at the heart of this issue exist the problem of conceptual knowledge representation method for models. Symbolic and sub-symbolic are two distinct paradigms which can be used to represent conceptual knowledge of cognitive robots . The simulation results of neural network and semantic network modelswhich are presented in this paper shown that both methods could be used for grounding of abstract words. Findings of comparison of these models state that neural network has the low storage capacity, combinatorial ambiguity, lack of compositional structure detail with more flexible behavior and immunity from symbol grounding problem. These attributes make it suitable for only small data repository models. Neural network model has to handle combinatorial ambiguity problem to ground abstract words. Semantic network with less flexible behaviour, restriction of strategic handling of symbolic grounding problem , high storage capacity and accuracy, integrity of compositional structure is more suitable for large data repository models.

The findings of this paper could be useful for investigation of abstract word representations at the modelling level in cognitive robots. The problem of grounding abstract words is related to many matters and concerns which are all interrelated like consideration of grounded cognition will solve symbol grounding problem. In the same way knowledge representation methods are also concerned with the symbol grounding problem.

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