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Modelling and Simulating Response Generation by a Computer Using a Rule-Based Approach Submission

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Abstract: The study presents a model of response generation by a computer using a rule-based approach. The rule-based approach, the underlying approach behind artificial intelligence has been modeled and simulated. A new model of response generation named the speech hierarchy model has been developed in the form of a mathematical framework which was then implemented as a tool. The tool simulates the process by which the human mind understands and visualizes a situation and then generates a response according to the context. The results of the simulation were near perfect although the tool does not parallel natural intelligence in terms of flexibility of stimulus and response.

Key words: Granularity, situation, context, speech hierarchy model, response, flexibility

INTRODUCTION

The study presents a new model for response generation by a computer. The concept of granularity was taken as the fundamental concept behind this approach. A natural language has four major granules by which text is created, namely, the alphabet, the word, the sentence and the paragraph. The completeness of a granule is achieved by applying rules to create, for example, the spelling of a word using alphabets in a fixed sequence. Similarly, a sentence is created by using intrasentence rules forming the structure of a sentence in a particular sequence. This sequence is very flexible in the case of Hindi as it has a context-free grammar. Further, a set of sentences together form a paragraph. This set of sentences are interlinked using intersentence rules which define the context of the paragraph and ultimately leads to an understanding of the paragraph.

Each granule further has a degree of participation in a coarser granule. Examples of such degrees are mentioned in the study. This idea of degrees of participation led to the development of the model in which a fuzzy element was found to correspond to each granule of a language. This led to the development of the speech hierarchy model which is based on fuzzy rules and a fuzzy semantic net of the various granules. The fuzzy semantic net was implemented to represent a real world situation in the computer in a visual form. An input sentence was given which was represented as a fuzzy semantic net. From this semantic net another semantic net was generated in the form of a response. From this response semantic net an output sentence was finally created.

Levels of granularity in a language (a rule-based approach): Granularity keet and Hobbs in linguistics refers to the "graininess" of a language. In a given language the finest grain is the alphabet. Alphabets combine using a set of Intraword rules to form a word. An intraword rule defines the spelling of the word. The next coarser grain is the sentence, formed by combining a set of Intrasentence rules applied on a set of words. The sentence forms the grain of a paragraph. A paragraph is created by combining a set of sentences using a set of Intersentence rules. Paragraphs taken together lead to text in the form of essays, books, etc. These rules have a direct correspondence with the real world situation in physical as well as conceptual terms.

MATERIALS AND METHODS

Context vs situation: A situation is a real world setting in which a human being finds himself at any point of time in his life. A situation involves one or more human beings interacting with their environment. When the human beings perceive the environment in their minds they usually represent the situation using some form of knowledge representation Brachman. The representation of the real world in the mind is analysed using

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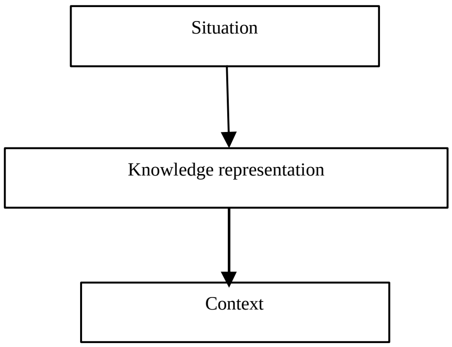

Fig. 1: The mapping between a real-world situation and the context

inferencing. The outcome of this inferencing can be considered to be the context of the interaction between the person and the environment. Further, the inferencing done by the human being may or may not lead to a linguistic response or a physical action by the persons. Thus, the mappings as shown in Fig. 1 exist in a situation with an intelligent system such as a human being, interacting with that situation.

The speech hierarchy model: The speech hierarchy model as shown in Fig. 2 is a model based on soft computing. The model relates elements of fuzzy theory with the corresponding levels of granularity in a language. The mapping of a phoneme to an alphabet is explained as by Prasad *et al.* (2012), Lakra *et al.* (2015a-c). The rest of the model has been developed into a mathematical framework presented next.

The speech hierarchy model: A spoken utterance has two components to it, one linguistic and the other paralinguistic. The basic element of a spoken utterance is the phoneme. Any one type of paralinguistic component is mapped to the linguistic component as a fuzzy mapping.

Human beings possess the ability to fathom variability Lakra *et al.* (2015a) by using fuzziness to represent degrees of variability (Lakra *et al.*, 2015a) in any paralinguistic parameter (Lakra *et al.*, 2015a). According to fuzzy theory, a continuum can be represented using the interval [0, 1]. Each variation of a paralinguistic parameter can be considered as a value lying in the interval [0, 1]. This value can then be mapped to the membership function of a fuzzy set and classified as a member of the fuzzy set. Thus, equstion:

$$\mu_A: X \rightarrow [0, 1] \tag{1}$$

Where:

X = Crisp set representing the values of a paralinguistic parameter and
μ = A membership function mapping $x \in X$ to the interval [0, 1] and to the fuzzy set A

The prevalent approach in speech processing has been the Acoustic-Phonetic Model. According to Eq. 1, there is a direct correspondence between the hierarchical elements of this model and the elements of fuzzy theory, thereby leading to a new soft computing based approach which has been christened as the speech hierarchy model. These correspondences are what are depicted in Fig. 2.

The phoneme and the corresponding alphabet: At the lowest level of granularity is the phoneme. A phoneme has two components to it, one linguistic and the other paralinguistic. The paralinguistic component is mapped to the linguistic component as a fuzzy mapping.

For example, consider the phoneme "u" uttered by n different speakers. Then the paralinguistic component of each speaker's utterance is a variation of the spoken phoneme. However, the linguistic component of each variation is the same that is the alphabet "u". Thus, there is a degree of membership of each variation in the fuzzy set representing the phoneme. This degree is represented by a fuzzy value in the interval [0, 1].

Generalizing, if P is a fuzzy set representing the paralinguistic content of a phoneme 2, then the degree of membership of a variation $v \in V$ in P is given by:

$$\mu_P: V \rightarrow [0, 1] \tag{2}$$

Each phoneme Π is mapped to an alphabet $\alpha \in A$ in a language Λ by the function p. Here, A is the set of alphabets of a language Λ. Therefore, P is also mapped to A. Thus:

$$p: \Pi \rightarrow \alpha \tag{3}$$

$$p: P \rightarrow \alpha \tag{4}$$

The word: At the next coarser level of granularity is a word W. The linguistic components of n phonemes that is a set of alphabets $\alpha_i \in A$, i = 1, .., n can be aggregated together to form a word. Now, each α_i is mapped by a fuzzy set P. Therefore, the paralinguistic component of a word can be considered as an aggregated set of a family of fuzzy sets P_i, i = 1, .., n. Thus:

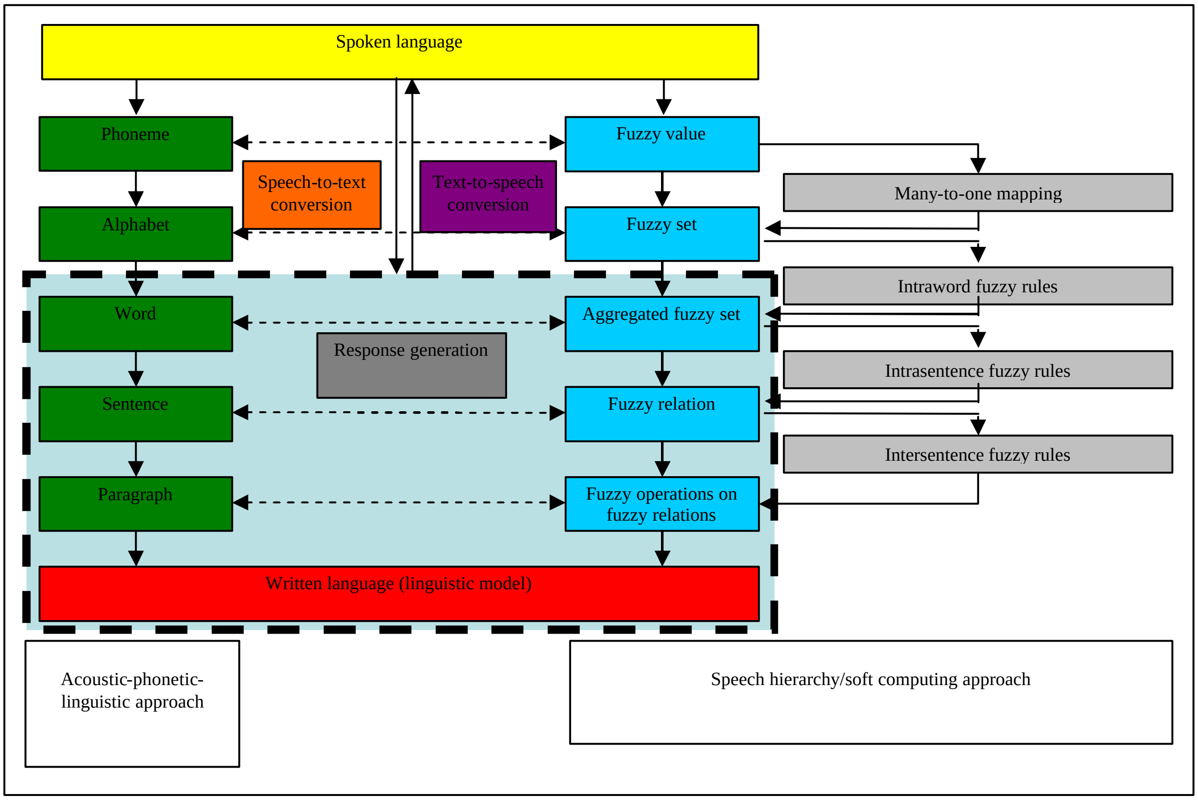

Fig. 2: The speech hierarchy model

$$W = h(P_i) \tag{5}$$

where, h is the aggregation function defined by the mapping:

$$h: [0, 1]^n \rightarrow [0, 1] \tag{6}$$

The sentence: At a still coarser level of granularity is a sentence S. Each sentence is a set of ordered words semantically related to each other. A sentence S is therefore, an aggregated set of a family of words W_g, g = 1, ... , r. That is:

$$S = h(W_g) \tag{7}$$

The ordering of the words in a sentence is represented by a fuzzy adjacency relation R that is:

$$R: W \times W \rightarrow [0, 1] \tag{8}$$

The semantics of a sentence are represented by a set of fuzzy rules termed as Intrasentence Rules ϕ_j, j = 1, ..., m, $\phi \in R$. Each ϕ is of the form ϕ: If W_1 is A and W_2 is B then $R(W_1, W_2)$ is C:

$$f\text{: If } W_1 \text{ is A and } W_2 \text{ is B then } R(W_1, W_2) \text{ is C} \tag{9}$$

The paragraph: At the highest level of granularity is a paragraph G which is a set of ordered sentences contextually related to each other. A paragraph G is an aggregated fuzzy set of a set of sentences S_d, d = 1, ..., s. Thus:

$$G = h(S_d) \tag{10}$$

The context: The context C of a paragraph G is represented by another set of fuzzy rules termed as intersentence rules ι_k, k = 1, ..., q, $\iota \in \Psi$. Thus, Ψ is a fuzzy relation J between subsets B of sentences. That is:

$$J: B \times B \rightarrow [0, 1] \tag{11}$$

An intersentence rule is a fuzzy rule between subsets B_1 and B_2 of two sentences S_1 and S_2. Each such subset is a word, a phrase or an intrasentence rule. Thus, Ψ: If B_1 is T and B_2 is U then $J(B_1, B_2)$ is V:

$$\psi\text{: If } B_1 \text{ is T and } B_2 \text{ is U then } J(B_1, B_2) \text{ is V} \tag{12}$$

Modifications to the context of a paragraph are carried out by applying fuzzy operations on the fuzzy sets, fuzzy relations and fuzzy rules as described above.

Using a semantic net to represent a situation: A fuzzy Semantic net is an extension of a semantic net wherein the concepts of degree of participation of a vertex and the degree of relationship of an edge are introduced.

Let G be a graph. The adjacency matrix of G with entries from the interval [0, 1] is called a fuzzy adjacency matrix of G. A Fuzzy Semantic Net Y is defined as a graph G (V, E) in which a fuzzy membership set M_Y is associated with V and a fuzzy adjacency matrix A_Y is associated with E.

Each vertex $v \in V$ in a fuzzy semantic net has a degree of membership associated with it which indicates its degree of participation in a fuzzy rule. A fuzzy rule is represented by an edge $e \in E$. The set of all fuzzy rules is represented by the fuzzy adjacency matrix A_Y. The set of degrees of participation of each $v \in V$ in respective fuzzy rules is represented by the fuzzy membership set M_Y.

Generating a response using a rule-based approach: In a dialog between two human speakers, there is an assertion or a question which may be collectively termed as a stimulus, by the first speaker and a response from the second speaker. Thus, there is a sequence of such stimulus-response pairs in a conversation. The response given by a human speaker is considered to be intelligent if it:

- Relevant to the context of the stimulus
- Takes into account the paralinguistic content of the spoken stimulus. That is, the second speaker gauges the gender, emotion, emphasis, speaking style, etc., of the spoken stimulus and then gives a response

There are two possible types of stimulus-response pairs:

- Question-answer pairs
- Assertion-response pairs

- Question-answer pairs
- Consider the following question-answer pair, e.g.,
- Question: What is your name(keyword)?
- Answer: My name is Sachit

Taking a closer look at this pair of sentences, it may be observed that there exist specific words in the answer which correspond to particular words in the question. This correspondence is shown in Table 1. Correspondence between words in a Question-Answer pair:

Assertion-response pairs: Consider the following assertion-response pair:

- Assertion: our spaceship is travelling very fast
- Paralinguistic content in the assertion
- Gender: female voice

Context or situation: Sitting in a spaceship, feeling G forces. Response: Madam, brace yourself very quickly. Similar to the case of a question-answer pair, there is a direct correspondence between pairs of words in the assertion and the response. In addition, some words in the response correspond to the paralinguistic content and some words indicate a degree of membership in the sentence other than 1. This is depicted in Table 2. Degrees of participation of words (objects) in a sentence (situation).

It is observable that in case of both the types of stimulus-response pairs, there exist certain rules based on which there is a direct correspondence between words and/or paralinguistic content in the stimuli and words and/or paralinguistic content in the responses. This leads to the concept of fuzzy response rules. A fuzzy response rule $\omega \in \Omega$ is a rule of the form:

$$\text{w: If } B_1 \text{ is M then } B_2 \text{ is N} \quad (12)$$

Table 1: Correspondence between words in a question-answer pair

Word from question	Corresponding word from answer
Your	My
What'	Name
Is	Is
Name	Sachit

Table 2: Degrees of participation of words (objects) in a sentence (situation)

Word in assertion	Degree of participation	Word in response	Degree of participation
Our	1.0	None	Nil
Spaceship is travelling and situation of Sitting in a spaceship, feeling G-forces	1.0	Brace yourself	1.0
Female voice	1.0	Madam	1.0
Very fast	0.9	Very quickly	0.88

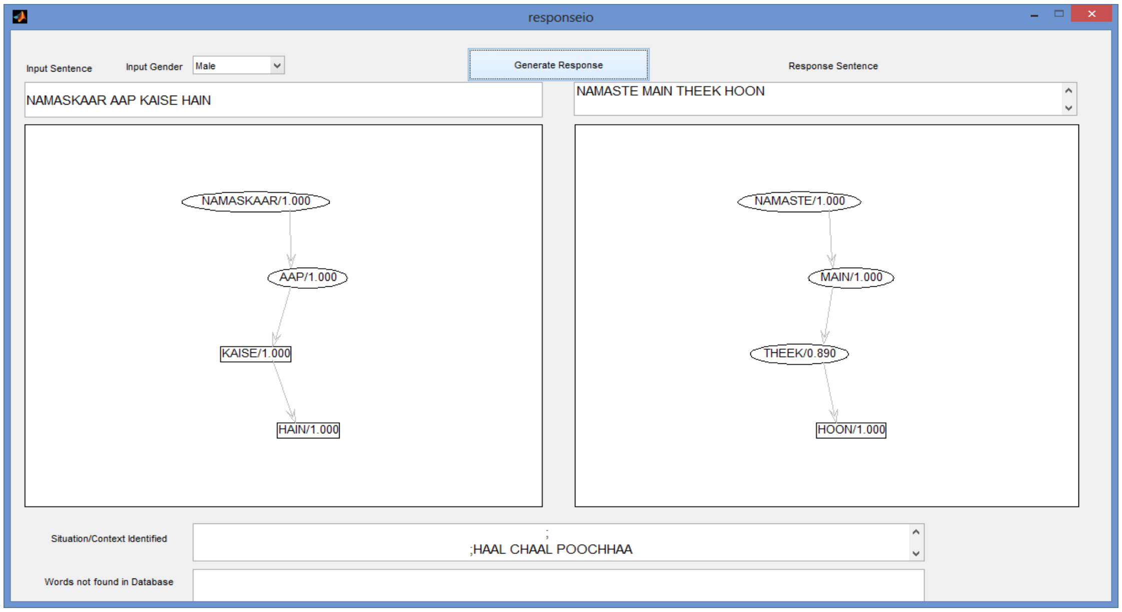

Fig. 3: Snapshot of the tool for simulating intelligent response generation

where, B is a subset of a sentence S. Thus, if a fuzzy semantic net Y_T is used to represent a stimulus sentence S_T, then a corresponding fuzzy semantic net Y_Z can be deduced using a set of fuzzy response rules Ω to represent the response sentence S_Z.

Based on the set of Intrasentence rules within the stimulus sentence and the response sentence, combined with the Response rules, a situation can be identified. This situation/context is associated with the collection of words and the rules combining the words and corresponds to an understanding or description of a situation arising in the mind of a human being in the form of a context.

RESULTS AND DISCUSSION

Table 3 gives a description of the test set and the accuracy of the results. Results of simulations for the tool for intelligent response generation. A rule based approach has been used to model the language Hindi. This approach is distinct from the approach followed in Natural Language Processing (NLP). NLP is based on a fixed sentence structure (SVO or SOV) and a grammar. However, human beings do not create a sentence which is based only on grammar. The human mind relates a sentence to a situation, represents it and then analyses it to infer a context. This set of steps are completely missing from NLP. The aim of this paper is to implement the process by which a situation gives a context to a human being and then the mind gives a response in an intelligent manner. It is this set of steps which have been simulated in the tool depicted in Fig. 3 shows the following stimulus-response pair:

Table 3: Results of simulations for the tool for intelligent response generation

Parameters	Values
Input sentence (stimulus) assumed to be given by	A human
Output sentence (response) assumed to be given by	A computer
Language	Hindi
Number of input sentences	50
Number of output sentences	50
Total number of sentences	100
Number of stimulus/response pairs	50
Number of situations	50 (1 situation per stimulus/response pair)
Number of Hindi words in dictionary	234
Length of shortest sentence	2 words
Length of longest sentence	8 words
Accuracy	100%

- Input Sentence in Hindi: NAMASKAAR AAP KAISAE HAIN?
- Input sentence translated into English: greetings, how are you?
- Output Sentence in Hindi: NAMASTE MAIN THEEK HOON
- Output Sentence translated into English: Greetings, I am fine

The tool generates a fuzzy semantic net from the Input Sentence followed by a response fuzzy semantic net as shown on the right side. The output sentence is obtained from the fuzzy semantic net representing the response. This is similar to the process in which the human mind receives spoken input of a sentence from another speaker, relates the recognized input words, identifies response words and then relates these words to give a response. Simultaneously, the mind performs inferencing from the input sentence and understands the situation in the form of context. The fuzzy semantic net represents the knowledge in the input sentence. The context identified has also been simulated which is:

- Context in Hindi: HAAL CHAAL POOCHHA
- Context (translation in english): asked about wellness

The individual words in sentences have been stored as part of a Knowledge Base-Database (KBDB) and the sentences have been created using intrasentence rules. These rules are stored in a separate table in the KBDB. The words in the input sentence have been related to response words in the output sentence using response rules which are also stored in a table. Each context has been related to a stimulus-response pair in yet another table in the KBDB (Fig. 3) Snapshot of the tool for simulating intelligent response generation.

CONCLUSION

Response generation has been simulated as part of the tool developed as part of this research work. The tool simulates how the brain visualizes and combines inputs using a fuzzy semantic network. Further, the mechanism by which the response is generated has also been simulated and the context has also been identified as part of the simulation. The tool represents simulation of handling context and natural language as done by an intelligent system.

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