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Machine Translation using Quantum Neural Network for Simple Sentences

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Abstract

This paper presents the machine translation system (MTS) which is based on the concept of self learning of semantically correct corpus using pattern recognition. The self learning process using pattern recognition is based on Quantum Neural Network (QNN). This is a novel and new approach to recognize and learn the corpus pattern using QNN. The paper 9ppresents systematically structure of the system, machine translation system and performance results. Present procedure performs the task of translation using its knowledge gained during learning by inputting pair of sentences from source to target language. Like a person, the system also acquires the necessary knowledge required for translation in implicit form from inputting pair sentences. The performance is also compared with other ANN approaches. It has also been shown that QNN requires less training time than the traditional ANN based training.

Keywords: Machine Translation, Semantic Translation, Syntactic Translation, QNNs, Pattern Recognition.

1. Introduction

Machine translation researchers are working with Natural Language Processing (NLP) since the computers were invented. Many researchers have tried to build the system which can understand multiple languages to translate from one source language to the target language. In their novel work, Chandola et al. described the use of pattern recognition for alignment and reordering of words for parts of tagging for Hindi language (Chandola et al, 1994).

This paper presents the usefulness of QNNs to perform machine translation (MT) using pattern recognition to increase in accuracy during the knowledge adoptability for machine translation. Here our main focus is to show the significant increase in accuracy with machine translation by using new approach of QNNs for pattern recognition to reorder the words for parts of speech tagging and their alignment during the machine translation.

QNNs based MT system is a possible solution to this problem, as these have ability to learn from examples by recognizing their pattern. If the translation of a sentence of such a QNN translation system is wrong, then it can be corrected and taught proper translation by a user without any expert technical knowledge.

2. Quantum Neural Network

The main motivation behind the study of QNN is the possibility to address the unrealistic situation as well as realistic situation, which is not possible with the traditional neural network. The main difference between conventional neural network and QNN is the form of the nonlinear activation functions of their hidden units. QNN has ability of classifying uncertain data (Purushothaman and Karayiannis et al, 1994, 1997; Kretzschmar et al. 2000). QNN is effective to classify indeterminate data because QNN has inherent fuzzy properties which can encode the sample information into discrete levels of certainty/ uncertainty.

In QNN model, the sigmoid function with various graded levels has been used as the activation function for each hidden neuron and is expressed as

$$sgm(x) = \frac{1}{n_s}\sum_{r=1}^{n_s}(1/(1+\exp\ \beta_h(x-\theta^r)\ ))$$

where, n_s denote the number of grades in the Sigmoid transfer functions and θ^r quantum interval of quantum level r, where $\beta_h$is slope factor, (Purushothaman and Karayiannis 1996, 1997).

3. Machine Translation Systems

Machine translation, a part of computational linguistics belongs to natural language processing (NLP) and is a hot issue in the computational society. Gap between the linguist and the computer programmer gives birth to problems like lexical ambiguity, syntactic and structural ambiguity, polysemy, induction, discourses, anaphoric ambiguity and different shade of meanings. English-to-Urdu machine translation systems were developed without considering the target language and also semantics are not included in existing systems.

Markovian model for machine translation is based on phrases rather than words and coupled with a phrase-to-phrase translation table. In this approach, translating a text-amount, to its most likely translation, is based on its available model parameters (Brown et al, 1994).

Rule based machine translation method for translating English sentences to Malayalam is employed (Rajan et al, 2009). In this work the core process is mediated by bilingual dictionaries and rules for converting source language structures into target language structures.

4. Proposed Machine Translation System

The proposed machine translation (MT) system has two different parts. One is for syntactic translation, another is for semantic translation. As source language goes into the MT system, it is first analyzed in the syntactic translation module and passes through the semantic translation module to deal with meaning of the words. Finally, the source language is translated into a target language. Each component is explained in detail in next sections.

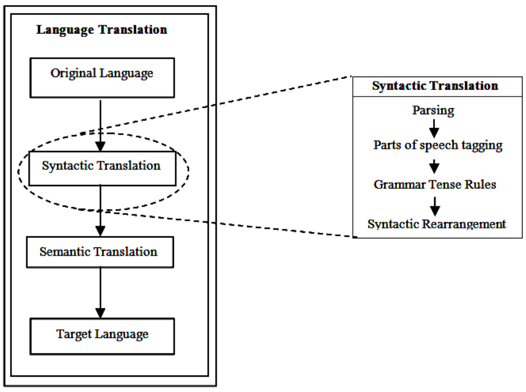

Figure 1: Architecture of MT System Model.

MT system can match according to the basic pattern type and separate it into various phrases based on the number of pattern types.

Parts-of-Speech--	Noun	Helping-Verb	Negative	Verb	Preposition	Article	Pronoun
English ----	Ram	Will	not	go	to	the	market
Devanagari-Hindi--	Ram	ga	nahi	jaye			Bazaar

Above example shows the sample of translated sentences, first line shows the parts of speech in each of the sentences under it and second line is the English sentence and the third line shows the Devanagari-Hindi translation without using grammatical rules as shown in Table 1. These examples of the syntactic translation process show the efficiency of analysis of the complex sentence without leaving the main factors. It allows the MT system to translate English into Devanagari-Hindi in more effective and accurate way.

Table 1: Lexicon Used For Each Part of Speech.

Noun (N)		**Helping Verb (HV)**		**Negative (Ne)**		**Verb (V)**		**Preposition (Pre)**		**Pronoun (Pro)**		**Article (A)**	
English	**Devanagari**	**English**	**Deva-nagari**	**English**	**Deva-nagari**	**English**	**Deva-nagari**	**Engl-ish**	**Deva-nagari**	**English**	**Deva-nagari**	**Engl-ish**	**Deva-nagari**
David	David	Will	ga	Not	nahi	Go	Jaye	To	ko	Market	bazaar	A	ek
Boy	larka	Can	sakta			Write	Likh	In	mai	Here	yahan	An	ek
He	vah	Was	tha			Working	Kaam ker raha hai			Office	karyalaya	The	
She	vah	Should	chahiye			Drink	Piye			School	vidyalaya		
They	ve	may	sakta			Came	Aaya			Home	ghar		

The proposed syntactic translation module analysis is done with pattern matching method for English sentence. Table 2 shows the process of the syntactic translation with example sentences used for training. In this example, English sentences are defined as six basic patterns. Based on the type of patterns, the syntactic translation module classifies the sentences into several phrases. Devanagari-Hindi sentences can be matched with one of the pattern and identify which pattern is correct for given Devanagari-Hindi sentences.

Table 2: Input sentences used for training.

#	**English - input sentences**	**Devanagari-Hindi – output sentences**
1.	David will not go to the market.	David bazaar nahi jayega.
2.	He was working in the office.	Wah karyalya mein kam kar raha tha.
3.	She should not go to the School.	Usko vidyalaya nahi jana chahiye.
4.	They can go home.	Ve ghar jaa sakte hain.
6.	Boy can write.	Larka likh sakta hai.

5. Quantum Neural Implementation of Translation Rules

As discussed in the above section 4, the strategy is to first identify and tag the parts of speech using the table 3 and then translate the English (source language) sentences literally into Devanagari-Hindi (target Language) as in sentence without any reordering. Once the literal translation is complete, the task remains to re-arrange them so as to make correct grammatical sense. The rules operate on parts of speech, independent of the meaning of the words. This suggests that the networks must learn the underlying symbolic manipulations. To facilitate this process, unique three-numeral codes to the parts of speech is assigned as shown in Table. 3.

Table 3: Numeric Codes for Parts of Speech.

Parts of speech (Sub Class)	**Resulting code**
Noun(N)	.100
Pronoun(Pro)	.102
Gerund(G)	.103
Verb(V)	.110
Helping verb(HV)	.111
Adverb(Adv)	.112
Article(A)	.123
Adjective(Adj)	.130
Preposition(Pre)	.140
Conjunction(Con)	.170
Interjection(In)	.180
Negative Word(Ne)	.220

Thus, the input code sequence is [.100 .111 .220 .110 .140 .123 .102] and the corresponding output is [.100 .102 .220 .110 .111 .000 .000]. Here dummy numeric code .000 is used as shown in figure 2.

The QNN which implements translation rule must recognize the pattern inherent in this reorganization. This is done by training the network on a sufficient number of coded input and output sentences chosen as the training set for pattern recognition.

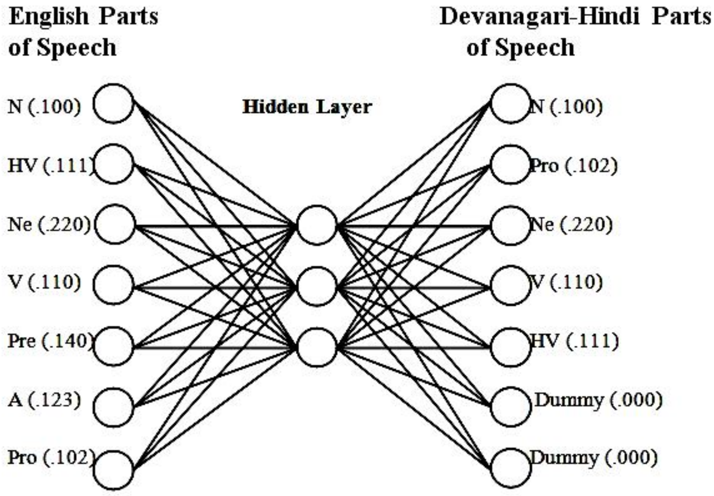

Figure 2: Architecture Diagram of QNN for Machine Translation.

Unlike in the above shown example, the network outputs are not perfectly integer. The outputs must be rounded to the nearest integer and some elementary error correction may be necessary to obtain the output symbolic codes. Even the network is likely to rearrange the position of the 3-numeral codes. By this, it learns the target language knowledge which is needed for semantic rearrangement, and also helps in parts of speech tagging, by pattern matching it is also helpful to adopt and learn the grammar rules up to a level.

6. Results and Discussion

All words in each language are assigned with a unique Numeric code, because the total number of parts of speech in one language did not exceed seven in the test. Figure 2 shows how this encoding scheme produced a total of seven numeric codes in the input layer and a total of seven numeric codes in the output layer of the QNN. All the errors of words in English and Devanagari-Hindi, sentence and parts of speech are evaluated and recorded using pattern recognition.

The results that are shown in this section are achieved after training with the 100 English sentences and their Devanagari-Hindi translations and the test performed with the system by the set of 1000 English sentences and their Devanagari-Hindi translations.

This paper proposed a new machine translation method which can combine the advantage of QNN. For training purpose only 100 simple sentences are used as input paired sentences, the experimental setup consists of 3 layers QNN with 7 nodes in input layer 3 nodes in hidden layer and 7 nodes in output layer. On a test set of 1000 sentences, experiments confirm that the accuracy rate of machine translation based on QNN is 98.261% for simple sentences, which is better than other bilingual translation methods like neural network based translation Table 4

Table 4: Comparison of Various Translation Systems.

Method	**Accuracy (%)**	**Iterations used in Learning the Network**
Proposed MT with QNN	**98.261**	**16.12**
Neural Network Based	86.667%	20.58

Experiments show that during learning process in QNN, there is decrease in indeterminacy of pattern recognition and increase in authenticity of pattern recognition. Hence, by using MT with QNN, the proposed system has achieved better bilingual translation with higher accuracy.

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