IMPROVING THE QUALITY OF GUJARATI-HINDI MACHINE TRANSLATION THROUGH PART-OF-SPEECH TAGGING AND STEMMER ASSISTED TRANSLITERATION

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ABSTRACT

Machine Translation for Indian languages is an emerging research area. Transliteration is one such module that we design while designing a translation system. Transliteration means mapping of source language text into the target language. Simple mapping decreases the efficiency of overall translation system. We propose the use of stemming and part-of-speech tagging for transliteration. The effectiveness of translation can be improved if we use part-of-speech tagging and stemming assisted transliteration. We have shown that much of the content in Gujarati gets transliterated while being processed for translation to Hindi language.

KEYWORDS

Stemming, transliteration, part-of-speech tagging

1. INTRODUCTION

Transliteration is a process that transliterates or rather maps the source content to the target content. While we design a translation model, transliteration proves to be an effective means for those words which are multilingual or which are not present in the training corpus. For a highly inflectional Indian language like Gujarati, naive transliteration i.e. direct transliteration without any rules or constraints, does not prove to be very effective. The main reason behind this is that suffixes get attached to the root words while forming a sentence.

We propose the use of stemming and POS-Tagging (i.e. Part-of-Speech Tagging) for the process of transliteration. Stemming refers to the removal of suffixes from the root word. Root word is actually the basic word to which suffixes get added. For example, in स्त्रीोमान्ती (striomaaNthii) the root is स्त्री and the suffix is अंती. These modules prove to be beneficial in the Natural Language Processing environment for morphologically rich languages.

The rest of the paper is arranged as follows: Section 2 describes the previous history of the related work which is followed by Section 3 which describes the proposed work. Evaluation and Results have been focused on in Section 4. Finally we conclude the paper with some enhancements for future work in Section 5.
2. LITERATURE REVIEW

Stemming was actually introduced by Lovins [1] who in 1968 proposed the use of it in Natural Language Processing applications. Two more stemming algorithms were proposed by Hafer and Weiss [2] and Paice [3]. Martin Porter [4] in 1980 suggested a suffix stripping algorithm which is still considered to be a standard stemming algorithm. Another approach to stemming was proposed by Frakes and Baeza-Yates [5] who proposed the use of term indexes and its root word in a table lookup. With the improvement in processing capabilities, there was a paradigm shift from purely rule-based techniques to statistical/machine learning approaches. Goldsmith [6][7] proposed an unsupervised approach to model morphological variants of European languages. Snover and Brent [8] proposed a Bayesian model for stemming of English and French languages. Freitag [9] proposed an algorithm for clustering of words using co-occurrence information. For Indian languages, Larkey et al. [10] used 27 rules to implement a stemmer for Hindi. Ramanathan and Rao [11] used the same approach, but used some more rules for stemming. Dasgupta and Ng [12] proposed an unsupervised morphological stemmer for Bengali. Majumder et al. [13] proposed a cluster based approach based on string distance measures which required no linguistic knowledge. Pandey and Siddiqui [14] proposed an unsupervised approach to stemming for Hindi, which was mostly based on the work of Goldsmith.

Considering the research work for part-of-speech tagging, Church [15] proposed n-gram model for tagging, which was then extended as HMM by Cutting et al. [16] in 1992. Brill [17] proposed a tagger based on transformation-based learning. Ratnaparkhi [18] proposed Maximum Entropy algorithm. Many researchers have recently proposed taggers with different approaches. Ray et al. [19] have proposed a morphology-based disambiguation for Hindi POS tagging. Dalal et al. [20] have proposed Feature Rich POS Tagger for Hindi. Patel and Gali [21] have proposed a tagging scheme for Gujarati using Conditional Random Fields. A rule-based Tamil POS-Tagger was developed by Arulmozhi et al. [22]. Arulmozhi and Sobha [23] have developed a hybrid POS-Tagger for relatively free word order language. Similarly for Bangla, Chowdhury et al. [24] and Sediqui et al. [25] have done significant research in the area of POS-Tagging. Antony and Soman [26] used kernel-based approach for Kannada POS-Tagging. Again a paradigm shift has been observed from purely rule-based schemes to statistical techniques. Taggers for many Indian languages have been proposed but still more work needs to be done as compared to European languages.

Moving towards the work for transliteration, Kirschenbaum and Wintner [27] have proposed a lightly supervised transliteration scheme. Arababi et al. [28] used a combination of neural net and expert systems for transliteration. Praneeth et al. [29] at LTRC, IIIT-H proposed a language-independent schema using character aligned models. Malik et al. [30] followed a hybrid approach for Urdu-Hindi transliteration. Joshi and Mathur [31] proposed the use of phonetic mapping based English-Hindi transliteration system which created a mapping table and a set of rules for transliteration of text. Joshi et al. [32] also proposed a predictive approach of for English-Hindi transliteration where the authors provided a suggestive list of possible text that the user entered. They looked at the partial text and tried to provide possible complete list as the suggestive list that the user could accept or provide their own input text. The use of transliteration has been proposed by many researchers for natural language processing and information retrieval applications.

3. PROPOSED WORK

Gujarati is a highly inflectional language as stated earlier. It has a free word-order. There are three genders in Gujarati- Feminine, Masculine and Neuter/Neutral. Suffixes get added to the stems giving the various morphological variants of the same root word.
We propose the use of stemming and POS-Tagging for the purpose of transliteration. Figure 1 shows our system.

![Figure 1. Transliteration assisted with stemming and part-of-speech tagging](image)

Many ambiguities are observed while we design a translation model from Gujarati-Hindi. One such ambiguity is differentiation of the suffix र is in different cases. Suppose we have the sentence

| रामे मने रिपोर्ट आपी. | → | राम ने मुझे रिपोर्ट दी। |
| Raame mane riport aapii. | (Meaning: Ram gave me the report.) |
| मारा घरे एक बिलाडी छे. | → | मेरे घर पर एक बिल्ली है। |
| Maara ghare ek bilaadii chhe | (Meaning: There is a cat at my home.) |

If these two sentences are carefully observed, the suffix serves different purpose. Hence it is the tag that makes a difference here. रामे is a proper noun and घरे is a locative noun. Hence to differentiate if a tagged corpus is applied, then during translation if the meanings are not available in the corpus and only the tags are available then the transliterated text will be the actual translation. Similarly, the suffix र छे poses an ambiguity.
We created a raw corpus of 5400 POS-tagged sentences and used 202 stemming and tagging rules to assist transliteration. The POS-Tagged corpus is a collection of text files having the sentences in the source language in the form- word_part-of-speech, e.g. वर्तिकण_NN. The strings in the source language are first checked in the tagged corpus so that the word class can be obtained and then stemming is applied which ensures the extraction of the correct root. Transliteration is hence first refined by these modules. So whenever there is an ambiguity in suffixes (i.e. stemming process), corresponding tags resolve the problem of transliteration. These modules can hence help in ambiguity resolution. If the corresponding tag is not found in the tagged corpus, naive transliteration is done where direct mapping from the source language into the target one is applied.

4. EVALUATION AND RESULTS

We tested our system on a total of 500 Sentences. The observed results are as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of Sentences tested</td>
<td>500</td>
</tr>
<tr>
<td>Total number of words tested</td>
<td>7500</td>
</tr>
<tr>
<td>Words for which transliteration and translation are same</td>
<td>4086</td>
</tr>
<tr>
<td>Percentage of words for which transliteration and translation are same</td>
<td>54.48</td>
</tr>
<tr>
<td>Number of words for which transliteration was wrong</td>
<td>518</td>
</tr>
<tr>
<td>Percentage of words for which transliteration was wrong</td>
<td>6.91</td>
</tr>
<tr>
<td>Percentage efficiency of transliteration</td>
<td>93.09</td>
</tr>
</tbody>
</table>

Table 1. Table showing evaluated results

Hence for 54.48% of Gujarati words translation and transliteration are same. The efficiency of our transliteration scheme is 93.09% (about 90%).

5. CONCLUSION AND FUTURE WORK

We followed a hybrid approach – a mix of rule-based and corpus-based approach, where we used POS-Tagged corpus and stemming rules to assist the process of transliteration. We achieved 93.09% overall efficiency of the transliteration scheme which makes it a promising approach. It was observed that 54.48% of the Gujarati words have the same translation and transliteration. Such a scheme not only reduces length of the corpus for the translation model.
but also it helps in ambiguity resolution. It can be used for other morphologically rich Indian languages as well. As an immediate extension to this work, we plan further to include machine learning approaches and focus on each and every aspect of the scheme so that more accuracy in the transliteration process can be achieved.

**REFERENCES**


AUTHORS

Juhi Ameta has completed her M.tech. in Computer Science from Banasthali Vidyapith, Rajasthan and is a Gold-medalist of her batch. She is currently working as an Assistant Professor at Cummins College of Engineering for Women, Pune, India. Her research interests include Natural Language Processing and Machine Translation. She has worked on EILMT Project funded by DIT, Govt. of India. Her research paper entitled “A Lightweight Stemmer for Gujarati” was published by CSI, Annual National Conference, Ahmedabad Chapter, December 2011.

Nisheeth Joshi is a researcher working in the area of Machine Translation. He has been primarily working in design and development of evaluation Matrices in Indian languages. Besides this he is also actively involved in the development of MT engines for English to Indian Languages. He is one of the expert empanelled with TDIL programme, Department of electronics Information Technology (DEITY), Govt. of India, a premier organization which foresees Language Technology Funding and Research in India. He has several publications in various journals and conferences and also serves on the Programme Committees and Editorial Boards of several conferences and journals.

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