International Research Journal of Human Resource and Social Sciences
ISSN(O): (2349-4085) ISSN(P): (2394-4218)
Impact Factor 6.924 Volume 9, Issue 09, September 2022
Website- www.aarf.asia, Email : editoraarf@gmail.com

A STUDY OF WORKING PRINCIPAL OF HOMOPHONE AMBIGUITY REDUCTION (SHAR)

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ABSTRACT

The objective of paper is to reduce the Homophone Ambiguity (åHomophone) from existing Speech Recognition Systems (SRS) in the Word Level Speech Recognition (WLSR) technique. There are various Speech Recognition Systems (SRS) available viz. Google Speech [18], Apple Siri Microsoft Speech Dragon Speech etc. The existing SRSs are significantly intelligent to perceive the exact homophone word in the Sentence Level Speech Recognition (SLSR) due to lexical analysis approach. But in the Word Level Recognition, the available Speech Recognition Systems (SRS) accept the proper homophone word only with dominating meaning and hence cannot resolve the limitation of homophone ambiguity to a large extent. The primary intention of the proposed research is to overcome this limitation from any existing Speech Recognition System (SRS). The String Comparing Algorithm for Ambiguity Reduction (SCAAR) comprises with supervised and unsupervised approaches to minimize Homophone Ambiguity (åHomophone) from a Speech Recognition System (SRS) in Word Level Speech Recognition (WLSR). This chapter contains the supervised approach and supervised learning approach to achieve this, where the system learns the correctness and incorrectness of homophone word(s). During this technique, 2940 homophone words are collected to construct the homophone dataset (Hds). Homophone Sets (hs) are then built up by Hierarchical Clustering Method (HCM). If the system detects a homophone word as an input, then the algorithm suggest an alternative or most suitable homophone word from the dataset.

KEYWORDS: Homophone Ambiguity Reduction (SHAR), Microsoft Speech,intelligent,Speech Recognition System.

INTRODUCTION

The Google Speech is deployed in all smart devices where Siri is used in Apple devices, and Microsoft Speech engine is available in WindowsOperating System [61]. The available speech recognition systems do not discriminate between two or more than two homophones in word level speech recognition therefore they cannot automatically choose a suitable alternative for a preferred homophone word [7]. It is also tested that Google Speech, Apple Siri, etc. continuously accepts the same homophone repeatedly in word level recognition. Thus the existing system does not accept the other homophone words from a same homophone set (hs). Let us consider 'Warm' and 'Worm'; the system recognizes 'Warm' in most cases. The probability of accepting the other homophone word within the same homophone set (hs) tends to zero. For resolving this, two thousands nine hundred and forty homophones are collected from several resources [105-118] and grouped in a homophone set (hs) by Hierarchical Clustering Method [33, 46]. Homophones from different sources [105-118] are collected and then merged in a single dataset with no redundancies [26]. In the Homophone Dataset (Hds), total two thousand nine hundred and forty homophone words are clustered into one thousand three hundred seventy one homophone set (hs). A homophone set (hs) number is allotted to same homophones within Hds. Few samples of Hds is shown in Table.4.1, and a partial part of the entire Hds is given in Appendix.V. When the system recognizes a homophone word, it extracts its hs along with its other homophone words. Thus the system can fetch all the homophones from a same homophone set and selects a suitable homophone word based on the proposed algorithm.

Table 1.1 Sample Homophone Dataset (Hds)

Set No.	Homophone Words	Total No of Members in each Set
1	Bite, Bight, Byte	3
2	Buy, By, Bye	3
3	Made, Maid	2
4	Tacks, Tax	2
5	To, Too, Two	3
6	Warm, Worm	2

Redundancy Removal from Homophone Dataset

Initially, it was not easy to collect the homophones. Many sources are there that contains unequal number of homophone words. During collecting the homophones [105-118], the following hindrances were overcome: 1. Most of the datasets do not contain all the homophones. 2. The same homophone set does not contain all the homophones in the different Homophone Dataset. Let us consider 'Bite', 'Bight' & 'Byte'. There are many homophone datasets that contain only 'Bite' & 'Byte', but 'Bight' is missing. The same homophone set contains dissimilar amount of homophones in different homophone resources [105-118]. A considerable amount of redundancy is found in the collected Hds and it is eliminated. After removing the redundancy of multiple homophones, the homophone set number is assigned to each group of homophones. Thus the homophone dataset (Hds) of 2940 homophones (h) is constructed with 1371 homophone set numbers (hs).

HIERARCHICAL CLUSTERING APPROACH

The Hierarchical Clustering Method (HCM) is concerned with hierarchy of cluster. The Hierarchical clustering creates clusters that have a predetermined arrangement from top-down or bottom-up approach [33, 46]. In the proposed system, each homophone (h) holds a homophone set (hs) number through which the other similar homophones can be accessed. From the Access Point (AP), the system starts accessing the homophone set (hs) and the other homophones of the input homophone. Figure 4.1 demonstrates the architecture of Homophone Dataset (Hds) of the proposed system with Hierarchical Clustering Method (HCM). In this proposed research, Access Point (AP) is associated with all the homophones (h). One homophone set (hs) is associated with more than one homophone words. If one homophone can be accessed from the AP, then the system fetches its other homophones from the system through the Homophone Set (hs). In Figure 1.2, the arrow marks indicates how theentire homophones are accessed from the Access Point (AP). Here h1, h2, and h3 are the homophone words from a same homophone set. From the AP, if h1 is accessed, then the system fetches its corresponding homophone set and subsequently the other homophones can also be accessed.

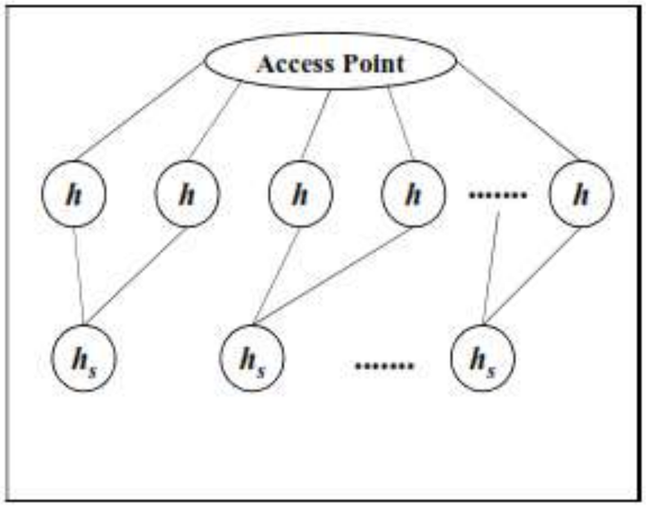


Figure 1.1 Hierarchical Clustering Approach for Proposed System

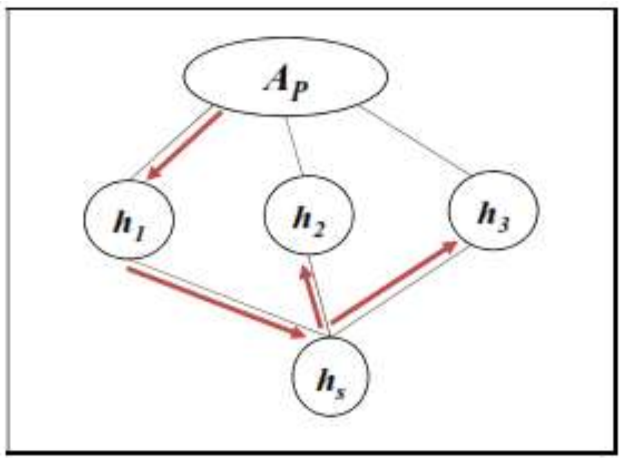


Figure 1.2 Flow Diagram of Accessing Homophone Words

Working Principal of proposed supervised approach for Homophone Ambiguity Reduction (SHAR)

The proposed system converts the Speech Input to a text. Let us consider a set of homophones, ‘Bite’, ‘Bight’ and ‘Byte’. When the user says ‘Bight’, the existing systems recognize ‘Bite’ instead of ‘Bight’ repeatedly. But after applying SHAR, the existing systems recognize ‘Bite’ and provide all other homophone alternatives to the user, and thereafter the user preferred homophone word is accepted and displayed by the system.

System Architecture of SHAR

Figure 1.3 displays the system architecture of Supervised approach for Homophone Ambiguity Reduction (SHAR) algorithm.

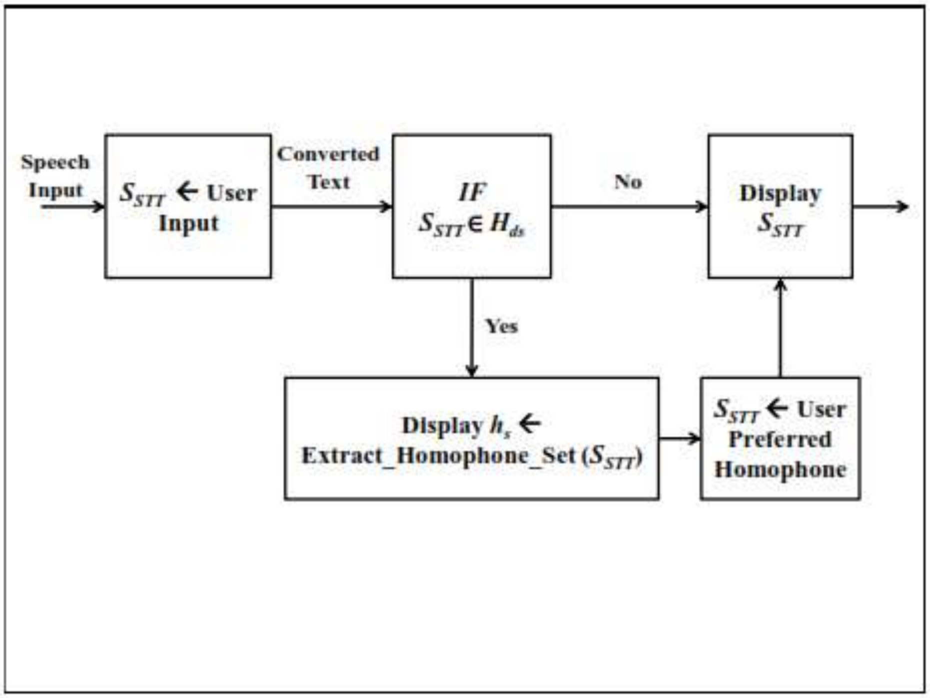
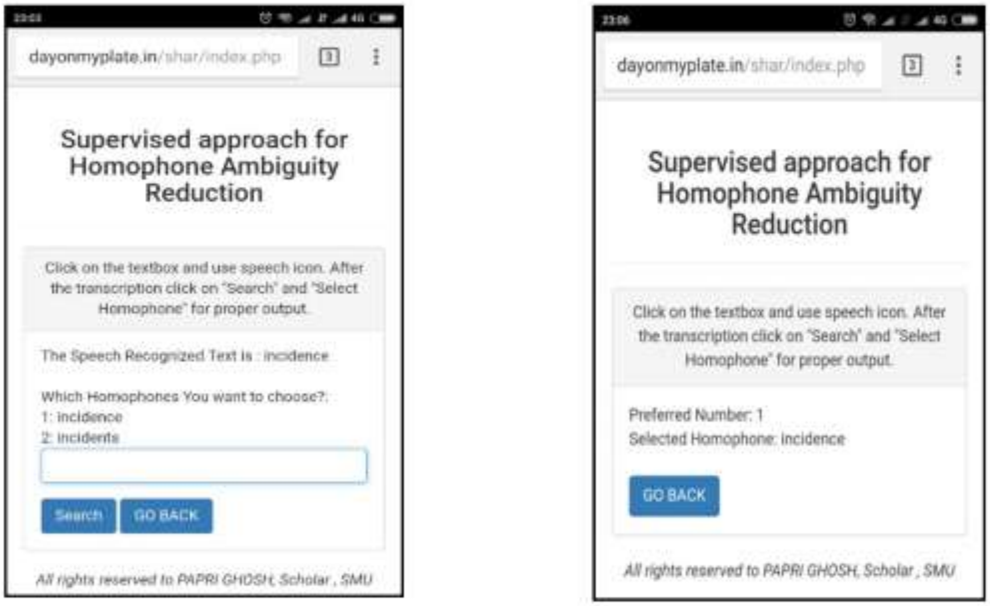


Figure 1.3 System Architecture of Supervised Approach for Homophone Ambiguity Reduction

The above flow diagram of SHAR shows how the system recognizes a string within the Hds. If it belongs to Hds, then the user can choose the appropriate homophone word based on the supervised approach.

Implementation of SHAR

The Supervised Approach for Homophone Ambiguity Reduction has implemented and shown in Figure 1.4. In Figure 1.4(a), the system selects all other homophones from the same homophone set (hs) and thereafter the system receives the user preferred alternative from the two homophones in a supervised manner and displays it to the user in Figure 1.4(b).



(a) Displays all Homophones from a same Homophone Set (b) Displays user preferred Homophone Figure 4.4 Snapshots of SHAR

The Supervised approach for Homophone Ambiguity Reduction does not follow any self-learning approach. In the next section, the homophone ambiguity reduction technique using self-learning approach is proposed using Artificial Immune Network (AINet) Algorithm.

Artificial Immune System

Natural Immune System (NIS) detects and eliminates infection from an animal body. Artificial Immune System (AIS) is a computational classification especially inspired and premeditated on the principles of Natural Immune System (NIS), which is exceedingly dispersed, adaptive and assorted method. In the Immune Network, two antibodies are attached through their idiotopes and receptors where the idiotopes and receptors constantly inhibit and stimulate each other in multifaceted regulatory networks. Being a multidisciplinary method, the research on this area inclined to awareness of immunology. The Artificial Immune System (AIS) considers the fundamental elements of the immune system and reveals various chief characteristics within a defined system. It is an instance of a developed system around the existing indulgent of the immune system.

Reward and Penalty Method

Reward and Penalty Method (RPM) connects with two categories of bifurcation of stimulation. The RPM helps a system to decide the advancement of a defined proclamation by several numerical values. Within this method, the system assigns reinforcement learning approach for improved actions. In this research, the RPM is considered as a tool of deciding the level of recognition for a correct or incorrect homophone word. The system assigns a reward value to a homophone if it is recognized correctly; otherwise, the penalty value is assigned. In the Artificial Immune System (AIS) based unsupervised algorithm, it is described how the RPM helps to decide whether a system recognized homophone word is correct or incorrect.

Artificial Immune Network

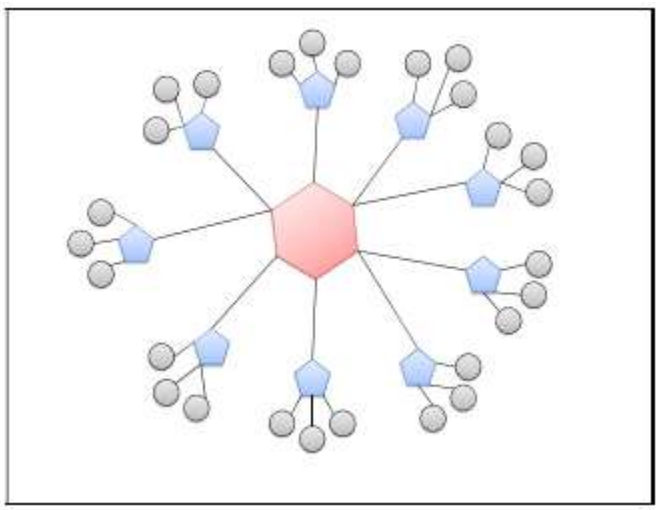


Figure 1.5 Sample Artificial Immune Network (AINet)

The Artificial Immune Network (AINet) is inspired by the Immune Network theory of Natural Immune System (NIS) that was proposed by Jerne in 1974 [15]. The immune system is constructed with synchronized network of different cells and molecules that is familiar to each other in the presence and absence of antigens. Timmis and Neil proposed a basic AINet algorithm in 2000. In their algorithm, they elaborated immune system components in a graphical network [77].

CONCLUSION

To eliminate the user intervention from the system, an unsupervised approach with Artificial Immune System that detects the correctness and incorrectness of a selected homophone word based on the human behaviour has been implemented in Chapter.5 by constructing a homophone dataset with 2940 homophones. As in this case, the user uses the system with immature homophone dataset at the initial stage, the probability of obtaining the incorrect homophone word is found to be high.To overcome the constraints of high probability of obtaining the incorrect homophone word at initial stage, an attempt has been made to mature the homophone dataset at early stage by using the Affinity Maturity Model as proposed in Chapter-6. For this, the homophone dataset is matured with a training process, wherein 100 (one hundred) e-books with approximately 38,00,000 (Thirty Eight Lakhs) words are processed by the proposed Affinity Maturity Model. More e-books can be processed to achieve further matured homophone dataset. The proposed unsupervised approach is tested after maturing the homophone dataset. Till now total 237 users has tested the proposed system with 50 highest prior and 50 non-highest prior homophone words after applying the maturity model and it is found that the proposed method is beneficial for the highest prior homophone word. . Compilation of both the algorithms mutually furnishes a new paradigm for any available Speech Recognition System (SRS) to minimize the memory requirement and homophone ambiguity (åHomophone) with immunological approach. The proposed system works as an e-accessory of every available speech recognition system without effecting the main algorithm and database of any conventional Speech Recognition System(s).

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