EDITORIAL PREFACE

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The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Starting with volume 3, 2012, IJHCI appears in more focused issues. Besides normal publications, IJHCI intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

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Abstract

Imaging systems introduce distortions and artifacts to the image. It is crucial to know the quality of the image before processing. In any image processing application it is important to know reliability of the imaging system and the quality metrics of the image acquired using the imaging system. This research aims to develop, reference image quality measurement algorithms for JPEG images. A JPEG image database was created and subjective experiments were conducted on the database. A newly proposed image pixel reduction technique was applied to the image to reduce its size. An attempt to design a computationally inexpensive and memory efficient feature extraction method has been developed along with the interleaving method. Subjective test results are used to train the neural network model, which achieves good quality prediction performance without any reference image. In particular the Elman neural network model predicts the mean opinion score of the human observer. The system has been implemented and tested for its validity. Experimental results show that the proposed algorithms have an accuracy rate of 90.23% for image quality recognition.

Keywords: Image Quality Assessment, Vertical Interleaving, Feature Extraction, Neural Network.

1. INTRODUCTION

Over the years, many researchers have taken different approaches to the problem of image quality assessment and have contributed significant research in the area with claims to have made progress in their respective domains. The topic of image quality assessment has been around for more than four decades, but the last few years have seen a sudden acceleration in progress and interest in this area. This corresponds with the rapid rise in interest in digital
imaging in general, driven by technological advances and by the ubiquity of digital images and videos on the Internet. Image quality assessment plays an important role in various image processing applications. The field of image and video processing generally deals with signals that are meant for human consumption, such as images or videos over the Internet [1]. An image or video may go through many stages of processing before being presented to a human observer and each stage of processing may introduce distortions that could reduce the quality of the final display. For example, images and videos are acquired by camera devices that may introduce distortions due to optics, sensor noise, color calibration, exposure control, camera motion etc [2]. After acquisition, the image or video may further be processed by a compression algorithm that reduces the bandwidth requirements for storage or transmission. Such compression algorithms are generally designed to achieve greater savings in bandwidth by letting certain distortions happen to the signal. Similarly, bit errors, which occur while an image is being transmitted over a channel or (rarely) when it is stored, also tend to introduce distortions. Finally, the display device used to render the final output may introduce some of its own distortion, such as low reproduction resolution, bad calibration etc. The amount of distortion that each of these stages could add depend mostly on economics and/or physical limitations of the devices [3].

One is obviously interested in being able to measure the quality of an image or video, and to gauge the distortion that has been added to it during different stages. One obvious way of determining the quality of an image or video is to obtain opinion from human observers as these signals are meant for human consumption [4]. However, such a method is not feasible not only due to the sheer number of images and videos that are available, but also because quality measurement techniques have to be embedded into the very algorithms that process images and videos, so that their output quality may be maximized for a given set of resources.

The goal of research in objective image quality assessment is to develop quantitative measures that can automatically predict perceived image quality [5]. Generally speaking, an objective image quality metric can play an important role in a broad range of applications, such as image acquisition, compression, communication, displaying, printing, restoration, enhancement, analysis and watermarking [5]. First, it can be used to dynamically monitor and adjust image quality. Second, it can be used to optimize algorithms and parameter settings of image processing systems. Third, it can be used to benchmark image processing systems and algorithms. In short, objective quality measurement (as opposed to subjective quality assessment by human observers) seeks to determine the quality of images or videos algorithmically. The goal of objective quality assessment (QA) research is to design algorithms whose quality prediction is in good agreement with subjective scores from human observers [7]. From the previous researches on image quality assessment it was observed that only few researchers have used the neural network to predict the quality of the image [8, 9]. In this paper, the various camera setting parameters and the feature extracted from the image database are used as the input to the neural network and the mean opinion score obtained from the subjects is used as the output to train the neural network model.

2. METHODOLOGY

An image acquisition process is subjected to many environmental concerns such as the position of the camera, number of cameras used, lighting sensitivity and background condition due to which the quality of the image is affected. The proposed system will predict the quality of the image using neural network models. The data are collected in three different locations with different environmental. Figure 1 shows the 3 different locations where the data collection were carried out. The images are captured using Sony DSR camera. While
collecting the data the aperture diameter (f1.0-f14), shutter speed (8-2000), ISO (160-3200) [8], light illumination and Pixel values are noted and used as features for the network model. Human observers can easily assess the quality of distorted images without using any reference image, for this reason the subjective evaluation of the image database is carried out [10]. There are 467 test images in the database, for collecting the mean opinion score 16 subjects were used and the pictures in the database are shown to them one by one. The subjects were asked to assign each image a quality score between 1 and 10 (10 represents the best quality and 1 the worst). The 16 scores of each image were averaged to a final Mean Opinion Score (MOS) of the image. Subjective experimental results on JPEG compressed images are used to train the network model. The proposed system has three processing stages namely preprocessing, feature extraction and classification. Figure 2 shows the block diagram of the proposed system. In the preprocessing stage the image is resized to reduce the computational time using interleaving method.

3. VERTICAL INTERLEAVING METHOD

Interleave is a pixel reduction technique where interleave method interleaves the image pixel either row-by-row or column-by-column. In this research a simple interleave method is proposed and carried out by comparing the pixel values either row-by-row or column-by-column. During the comparison the maximum pixel value will be taken and the minimum value is discarded. If the pixel value is equal then any one pixel value is taken. The pixel values are compared column by column in this research and hence the proposed method is called vertical maximum interleaving. Figure 3 shows the image before interleaving and after interleaving. The vertical maximum interleaving method algorithm is as follows.

Vertical Maximum Interleaving method Algorithm:

Step 1: Acquire the segmented region
Step 2: Compare the pixel value of each alternative columns with the corresponding adjacent column and find the maximum value.

FIGURE 1: Three different Data collection locations

FIGURE 2: Block Diagram of Proposed System
Step 3: If both the pixel value are same then take any one value.
Step 4: Acquire the new vertical interleaved image using Step 2 and Step 3
After applying interleaving method on the image and the features are extracted from the input images.

**FIGURE 3**: Vertical Maximum Interleaving method

4. FEATURE EXTRACTION

JPEG is a block DCT-based lossy image coding technique. It is lossy because of the quantization operation applied to the DCT coefficients in each $8 \times 8$ coding block. Both blurring and blocking artifacts may be created during quantization. The blurring effect is mainly due to the loss of high frequency DCT coefficients, which smoothes the image signal within each block. Blocking effect occurs due to the discontinuity at block boundaries, which is generated because the quantization in JPEG is block-based and the blocks are quantized independently. Blurring and blocking are the most significant artifacts generated during the JPEG compression process [11]. We denote the test image signal as $x(m,n)$ for $m \in [1,M]$ and $n \in [1,N]$. Calculating the differencing signal along each horizontal axis:

$$d_h(m,n) = x(m,n) - x(m+1,n), n \in [1,N-1]$$  \hspace{1cm} (1)

First, the blocking estimated as the average differences across block boundaries:

$$B_h = \frac{1}{M(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N-1} |d_h(i,j)|$$  \hspace{1cm} (2)

Secondly, the blurring in the image is evaluated using two activity measures. The first activity measure is the average absolute difference between in-block image samples and is calculated as:

$$A_h = \frac{1}{8(MN-1)} \sum_{i=1}^{M} \sum_{j=1}^{N-1} |d_h(i,j)| - B_h$$  \hspace{1cm} (3)

The second activity measure is the zero-crossing (ZC) rate. Define $n \in [1,N-2]$,\n
$$z_h(m,n) = \begin{cases} 1 & \text{horizontal ZC at } d_h(m,n) \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (4)

Then the horizontal ZC rate can be calculated from the below equation

$$Z_h = \frac{1}{M(N-2)} \sum_{i=1}^{M} \sum_{j=1}^{N-2} z_h(m,n)$$  \hspace{1cm} (5)
Using similar methods, we calculate the vertical features of $B_v$, $A_v$, and $Z_v$. Finally, the overall features are given by:

$$B = \frac{B_n + B_v}{2}, A = \frac{A_n + A_v}{2}, Z = \frac{Z_n + Z_v}{2}.$$  \hspace{1cm} (6)

These feature extraction methods are computationally inexpensive and memory efficient [12].

5. NEURAL NETWORK MODELING

Artificial Neural Network (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain [13]. To classify the image based on its quality an Elman neural network has been developed. Typical Elman network has one hidden layer with delayed feedback. The Elman neural network is capable of providing the standard state-space representation for dynamic systems [14]. The neural network architecture has three layers consisting of an input layer, one hidden layer and an output layer. To predict the quality of the image a simple neural network model using error back propagation was developed. The network model has 8 input neurons representing the features (aperture diameter, shutter speed, pixel value, ISO, light illumination, $B$, $A$ and $Z$), 3 hidden neurons and 4 output neurons. The network initial weights are chosen randomly between 0 to 1. The network is trained with 60% of samples i.e., 281 samples and tested with the remaining 40% i.e., 186 samples. For each trail, the network is trained for five times (with five different initial weights) and the mean classification rate, minimum and maximum epochs are recorded. In the experimental analysis, five such trails were made and the results are tabulated in Table 1.

<table>
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<th>Number of samples used for testing: 186</th>
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<td>Total Samples: 467</td>
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<table>
<thead>
<tr>
<th>Number of Input neurons: 8</th>
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<td>Number of output neurons: 4</td>
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<td>2</td>
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<tr>
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</tr>
<tr>
<td>Average</td>
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| TABLE 1: Network architecture for image quality prediction |

6. RESULTS AND DISCUSSION

The learning rate, momentum factor, training and testing tolerance for the image quality prediction network are also shown in Table 1. From Table 1 it is observed that the maximum classification accuracy for the developed network model is 92.46% and the minimum
classification rate is 89.19%. The maximum epoch value obtained for the developed network model is 8466 and the minimum epoch value is 5015. The mean epoch value for the developed network model is 8713. The interleaving method showed improvements in reducing the processing time. Experimental results shows that the neural network model correlates highly with the mean opinion scores based on the classification results obtained.

7. CONCLUSION

The current research in image quality assessment has come a long way from its beginning few decades ago. This work presented an automated system for objective assessment of image quality a new approach for image quality assessment using neural network model was proposed. Using the Elman neural network model the quality of the images where obtained. A new image interleaving algorithm was proposed in this paper. The image interleaving method reduces the pixel values and hence the processing time was reduced. The proposed system has a mean classification accuracy of 90.23%. The experimental results confirm that the developed system can recognize the quality metrics of the image correctly. In future a neural network based controller is proposed to be used to control the camera parameters to obtain good quality image.

8. ACKNOWLEDGMENT

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9. REFERENCES


Parameters Optimization for Improving ASR Performance in Adverse Real World Noisy Environmental Conditions

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Abstract

From the existing research it has been observed that many techniques and methodologies are available for performing every step of Automatic Speech Recognition (ASR) system, but the performance (Minimization of Word Error Recognition-WER and Maximization of Word Accuracy Rate- WAR) of the methodology is not dependent on the only technique applied in that method. The research work indicates that, performance mainly depends on the category of the noise, the level of the noise and the variable size of the window, frame, frame overlap etc is considered in the existing methods.

The main aim of the work presented in this paper is to use variable size of parameters like window size, frame size and frame overlap percentage to observe the performance of algorithms for various categories of noise with different levels and also train the system for all size of parameters and category of real world noisy environment to improve the performance of the speech recognition system.

This paper presents the results of Signal-to-Noise Ratio (SNR) and Accuracy test by applying variable size of parameters. It is observed that, it is really very hard to evaluate test results and decide parameter size for ASR performance improvement for its resultant optimization. Hence, this study further suggests the feasible and optimum parameter size using Fuzzy Inference System (FIS) for enhancing resultant accuracy in adverse real world noisy environmental conditions.

This work will be helpful to give discriminative training of ubiquitous ASR system for better Human Computer Interaction (HCI).

Keywords: ASR Performance, ASR Parameters Optimization, Multi-Environmental Training, Fuzzy Inference System for ASR, Ubiquitous ASR System, Human Computer Interaction (HCI).

1. INTRODUCTION

Many Speech User Interface (SUI) based applications are now a part of daily life. However, a number of hurdles remain to making these technologies ubiquitous [1]. In light of the increasingly mobile and socially connected population, core challenges include robustness to additive background noise, convolutional channel noise, room reverberation and microphone mismatch [2, 3]. Other challenges include the ability to support the world’s range of speakers, languages and dialects in speech technology.
Automated speech recognition (ASR) is the foundation of many speech and language processing applications. ASR technology includes signal processing, optimization, machine learning, and statistical techniques to model human speech and understanding.

This complete work focuses on following major issues for ASR performance improvement,

- Methodologies at pre-processing i.e. back-end level;
- Techniques at signal processing front-end for feature parameter extractions;
- Multi-environment training for Environment Adaptation and reducing the difference between training and testing environment;
- Variable parameter optimization using Fuzzy logic that is similar to the way of human thinking. Fuzzy sets are successfully applied for speech recognition due to their ability to deal with uncertainty.

This paper focuses on the last issue, as first three issues are already analyzed and results are submitted for publication.

This work may be extended to train the system for multi-user and English language speakers from various countries.

2. FUZZY LOGIC AND FUZZY INFERENCE METHODOLOGY

The concept of fuzzy logic [4] to present vagueness in linguistics, and further implement and express human knowledge and inference capability in a natural way. Fuzzy logic starts with the concept of a fuzzy set.

A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A Membership Function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse. Let X be the universe of discourse and x be a generic element of X. A classical set A is defined as a collection of elements or objects x ∈ X, such that each x can either belong to or not belong to the set A, A ⊆ X. By defining a characteristic function (or membership function) on each element x in X, a classical set A can be represented by a set of ordered pairs (x, 0) or (x, 1), where 1 indicates membership and 0 non-membership. Unlike conventional set mentioned above fuzzy set expresses the degree to which an element belongs to a set. Hence the characteristic function of a fuzzy set is allowed to have value between 0 and 1, denoting the degree of membership of an element in a given set. If X is a collection of objects denoted generically by x, then a fuzzy set A in X is defined as a set of ordered pairs.

The Fuzzy System has Five Parts of the Fuzzy Inference System

- Fuzzification of the given set of variables
- Application of the fuzzy operator (AND or OR) in the antecedent
- Implication from the antecedent to the consequent
- Aggregation of the consequents across the rules
- Defuzzification

Fuzzy Inference System

In this context, Fuzzy Inference Systems (FIS), also known as fuzzy rule-based systems, are well-known tools for the simulation of nonlinear behaviors with the help of fuzzy logic and linguistic fuzzy rules. There are some popular inference techniques developed for fuzzy systems, such as Mamdani [5], Sugeno [6], Tsukamoto [6]. Mamdani FIS is selected to use in this experimental study.

3. PROPOSED METHODOLOGY

From the literature study and analysis of speech processing methods it is observed that performance of the speech processing technique and the word recognition accuracy of a speech recognition system is dependent on windowing and frame size frame overlap size of a speech sample [7], recoding – training – testing environment, technique/s used at front-end and back-end of a system.
Therefore this work uses variable size of windowing, framing and frame overlap size, and the performance evaluation is done on every step of a system model from front-end and back-end techniques.

- Speech samples of digits, zero to nine are recorded from different ten Indian English speaking persons (five males and five females) and multiple utterances, in real world noisy environment with sampling frequency 8 kHz and time duration 3 sec.
- First, these samples are checked for whether voiced / invoiced / or silence [8]. Only voiced samples are considered and others are discarded.
- In the pre-processing steps, noise is removed using filters and enhanced [9,10] using Wiener-Type Filter algorithm [11]. This algorithm is tested on different window size, frame size frame overlap size and for different category of noisy environment (Back-end level).
- SNR improvement test is performed. Results are given in Table: 1-5.
- Features are extracted using MFCC front-end technique [12, 13]. Features are extracted using different window and frame size.
- Further these feature parameters are passed to Hidden Markov Model (HMM) for training and followed by recognition [14]. Here the aim is to train the system for all types of environment (Multi-environment training) to improve the word recognition accuracy therefore, system is trained for all variety of samples like samples recorded at clean environment (inside glass cabin), samples recorded at all category of real world noise (out-side of room and at crowded places), samples after applying traditional noise removal filters, samples after applying speech enhancement algorithms etc.
- Accuracy is computed using Word recognition rate separately for different window and frame size. Results are given in Table: 1-5.
- This experiment is performed adjusting variable parameters like window, frame and frame overlap size manually (using computer program) to find out improvement in word recognition accuracy using iterative method. Please refer Table: 1-5
- The aim of this experiment is to find-out variable parameters size to optimized accuracy therefore a ruled base Fuzzy Inference System (FIS) from MatLab [15] is used.
- Window size and Frame overlap size in % and SNR as an environment are sent to the FIS as input parameters and Word recognition accuracy is computed as output. Rules are framed to compute the output.

4. EMPIRICAL PROCESS FOR FUZZY INFERENCE SYSTEM (FIS)

FIS uses following parameters,

4.1 Parameter List:

1. Hamming Window Size: 240-270 step size 10 (240, 250, 260, 270)
2. Frame Overlap percentage: 20-60 % Step size 5% (20, 25, 30, 35, 40, 45, 50, 55, 60)
3. Window Size is calculated using following equation:
   \[
   \text{Window Size} = \text{Window length} \times \text{Sampling Frequency} \quad (\text{Window length is 20 ms})
   \]
4. Variable Frame Size is obtained using equation:
   \[
   \begin{align*}
   \text{Frame Size} &= \frac{\text{Speech Sample Length}}{\text{Size of Hamming Window}} \times \text{Frame Overlap %}
   \end{align*}
   \]
5. Word Recognition Accuracy is computed using equation:

\[
\text{Word Recognition Accuracy} = \frac{\text{Number of Words Recognised}}{\text{Number of Words Tested}} \times 100\%
\]

4.2 Fuzzy Inference System (FIS):

FIS is set using the following parameters:

[System]
Name='SpeechAccuracy'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=5
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

Three inputs are selected in the system, SNR value is passed for the Environment, Hamming windows size as WinSz and Frame overlap percentages as FrOver. Input parameters, their membership function and ranges as follow.

[Input1]
Name='Environment'
Range=[10 50]
NumMFs=3
MF1='VNoisy':trimf,[10 20 40]
MF2='Noisy':trimf,[20 30 40]
MF3='Clean':trimf,[35 50 66]
Environment is defined as the value based on SNR, 10-20 dB is Very Noisy, 20-35 dB is Noisy and 35-50 dB is assumed for clean environment.

[Input2]
Name='WinSz'
Range=[240 270]
NumMFs=3
MF1='Small':trimf,[225 240 250]
MF2='Medium':trimf,[250 255 260]
MF3='Large':trimf,[260 270 282]
Window size is considered in three ranges Small, Medium and Large with ranges 240-250, 255-260 and 260-270 respectively.

[Input3]
Name='FrOver'
Range=[20 60]
NumMFs=3
MF1='Small':trimf,[4 20 40]
MF2='Medium':trimf,[40 50 55]
MF3='Large':trimf,[50 60 76]
Frame overlap percentage is considered in three ranges Small, Medium and Large with ranges 20-40, 40-50 and 50-60 respectively.
[Output 1]
Name='Accuracy'
Range=[95 100]
NumMFs=3
MF1='Good':'gaussmf',[0.8493 95]
MF2='Better':'gaussmf',[0.8493 97.5]
MF3='Best':'gaussmf',[0.8493 100]

The Word recognition Accuracy is the final output. It is considered as Good, Better and Best in the expected range of 95 to 100%.

After defining input, output and their membership functions, rules are framed and weights are assigned as given below

[Rules]
3 0 0, 2 (0.5) : 1
3 0 2, 3 (0.75) : 1
3 2 3, 3 (1) : 1
0 0 2, 2 (0.5) : 1
0 2 0, 2 (0.5) : 1

- If (Environment is Clean) then (Accuracy is Better) (0.5)
- If (Environment is Clean) and (FrOver is Medium) then (Accuracy is Best) (0.75)
- If (Environment is Clean) and (WinSz is Medium) and (FrOver is Medium) then (Accuracy is Best) (1)
- If (FrOver is Medium) then (Accuracy is Better) (0.5)
- If (WinSz is Medium) then (Accuracy is Better) (0.5)

Final step is defuzzification, output accuracy is observed for different rules and crisp value is obtained using centroid - DefuzzMethod.

Observations and output results are given in Results and Discussion section.

5. RESULTS AND DISCUSSION
Frame size, SNR and accuracy results for different Hamming window and frame overlap % are given in table 1-5. Tables are given at the end of paper.

Table 1: SNR & Accuracy Test results for different Hamming Window Size, Frame Size and Frame Overlap % for same sample recorded at Real World Environment Noise

Table 2: SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 240 for different samples at Real World Environment Noise

Table 3: SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 250 for different samples at Real World Environment Noise

Table 4: SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 260 for different samples at Real World Environment Noise

Table 5: SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 270 for different samples at Real World Environment Noise
FIS Results

- Five rules are set to compute the Accuracy as an output as shown in fig: 1.
- Using the default values output of rules are viewed as shown in fig: 2 and crisp value of accuracy is observed.

Output of rules are viewed and crisp value of accuracy is observed by changing input values as shown in fig: 3.

---

**Fig 1:** Rules sets for Accuracy Optimization

**Fig 2:** Output of Rules and Defuzzification (Parameter Set 1)
6. CONCLUSION
The assumption for this study was that the word recognition accuracy not only depends on the adverse environment conditions but variable size of hamming window, frame overlap and frame length also. It is proved by using traditional algorithm methods and calculations using different size of parameters as well as fuzzy system.

The improved word recognition accuracy is observed using hybrid signal enhancement method as compared to results shown in previous literature.

From the tabular data, for all hamming window size, SNR gradually improved till 50 % frame overlap but after going down. There is variation in word recognition accuracy calculated for different hamming window size and frame size. The better accuracy is observed in between 45-55 % frame overlap.

From FIS simulation results, the feasible parameter size for accuracy improvement is found in ranges, that clean environment SNR between 40-50 dB, Hamming window size should be medium 250-260 ms and frame overlap percentage between 40-55 %.

The optimized parameter size for best accuracy is observed by clean environment SNR above 45 db, hamming window size 255 ms and frame overlap percentage 50.6

7. REFERENCES


### Result Tables

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<th>Hamm Win Size</th>
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**TABLE 1**: SNR & Accuracy Test results for different Hamming Window Size, Frame Size and Frame Overlap % for same sample recorded at Real World Environment Noise.
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**TABLE 2:** SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 240 for different samples at Real World Environment Noise

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**TABLE 3:** SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 250 for different samples at Real World Environment Noise
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<td></td>
<td>Accuracy</td>
<td>70.3437</td>
<td>88.3372</td>
<td>89.0639</td>
<td>88.7544</td>
<td>90.0423</td>
<td>98.9302</td>
<td>98.4291</td>
<td>98.1957</td>
<td>85.5299</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>5.1934</td>
<td>13.4992</td>
<td>17.5608</td>
<td>22.2304</td>
<td>29.4272</td>
<td>40.7495</td>
<td>46.3925</td>
<td>32.2664</td>
<td>23.7535</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>70.3437</td>
<td>88.3372</td>
<td>89.0639</td>
<td>88.7544</td>
<td>90.0423</td>
<td>98.9302</td>
<td>98.4291</td>
<td>98.1957</td>
<td>85.5299</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>73.6737</td>
<td>88.1840</td>
<td>88.5332</td>
<td>89.4204</td>
<td>93.3996</td>
<td>99.3798</td>
<td>98.1498</td>
<td>98.0034</td>
<td>93.6781</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>80.6190</td>
<td>89.4388</td>
<td>93.8953</td>
<td>89.6268</td>
<td>93.4655</td>
<td>98.7188</td>
<td>97.3934</td>
<td>97.7700</td>
<td>82.6416</td>
</tr>
</tbody>
</table>

**TABLE 4:** SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 260 for different samples at Real World Environment Noise
<table>
<thead>
<tr>
<th>Digit &amp; SNR</th>
<th>Frame Overlap %</th>
<th>20</th>
<th>25</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50</th>
<th>55</th>
<th>60</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy</td>
<td>84.1680</td>
<td>92.7069</td>
<td>85.6339</td>
<td>84.4252</td>
<td>85.0631</td>
<td>97.4070</td>
<td>96.1970</td>
<td>96.6073</td>
<td>79.7440</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>82.1904</td>
<td>83.0485</td>
<td>92.5670</td>
<td>88.0164</td>
<td>89.9434</td>
<td>98.4571</td>
<td>97.4012</td>
<td>98.1314</td>
<td>87.8278</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>86.6888</td>
<td>82.8465</td>
<td>91.5688</td>
<td>89.7664</td>
<td>94.9054</td>
<td>98.2860</td>
<td>99.3911</td>
<td>98.7690</td>
<td>89.3470</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>80.5280</td>
<td>81.9218</td>
<td>86.3983</td>
<td>88.9572</td>
<td>93.4516</td>
<td>93.3655</td>
<td>98.6892</td>
<td>97.4008</td>
<td>79.4203</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>10.5104</td>
<td>14.4805</td>
<td>18.0018</td>
<td>23.3613</td>
<td>29.5838</td>
<td>1.8883</td>
<td>9.7839</td>
<td>34.0240</td>
<td>44.8241</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>84.0832</td>
<td>88.3311</td>
<td>88.2088</td>
<td>93.4452</td>
<td>93.7806</td>
<td>94.3431</td>
<td>97.3289</td>
<td>96.8648</td>
<td>96.3668</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>10.4099</td>
<td>14.6564</td>
<td>19.1060</td>
<td>23.1816</td>
<td>28.4106</td>
<td>38.4336</td>
<td>44.6465</td>
<td>34.5082</td>
<td>26.6326</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>83.2792</td>
<td>89.4040</td>
<td>93.6194</td>
<td>92.7264</td>
<td>90.0616</td>
<td>98.3973</td>
<td>97.3294</td>
<td>96.1721</td>
<td>95.8774</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>10.4099</td>
<td>14.6564</td>
<td>19.1060</td>
<td>23.1816</td>
<td>28.4106</td>
<td>38.4336</td>
<td>44.6465</td>
<td>34.5082</td>
<td>26.6326</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>83.2792</td>
<td>89.4040</td>
<td>93.6194</td>
<td>92.7264</td>
<td>90.0616</td>
<td>98.3973</td>
<td>97.3294</td>
<td>96.1721</td>
<td>95.8774</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>11.4981</td>
<td>15.9106</td>
<td>17.2896</td>
<td>22.6451</td>
<td>28.7847</td>
<td>38.0097</td>
<td>41.0257</td>
<td>33.8041</td>
<td>23.9987</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>91.9848</td>
<td>97.0547</td>
<td>84.7190</td>
<td>90.5804</td>
<td>91.2475</td>
<td>98.4223</td>
<td>99.4360</td>
<td>98.2711</td>
<td>86.3953</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>97.4616</td>
<td>98.5260</td>
<td>80.7643</td>
<td>83.7192</td>
<td>86.7267</td>
<td>96.2481</td>
<td>98.5072</td>
<td>97.9436</td>
<td>87.7254</td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>9.6448</td>
<td>12.9770</td>
<td>17.0795</td>
<td>22.1698</td>
<td>29.4271</td>
<td>37.7130</td>
<td>38.8767</td>
<td>29.3890</td>
<td>20.1720</td>
</tr>
<tr>
<td></td>
<td>Accuracy</td>
<td>87.1584</td>
<td>89.1597</td>
<td>83.6896</td>
<td>88.6792</td>
<td>93.2839</td>
<td>96.7399</td>
<td>98.7512</td>
<td>97.3503</td>
<td>82.6192</td>
</tr>
</tbody>
</table>

**TABLE 5:** SNR & Accuracy Test results for different frame size and frame overlap % and Window Size 270 for different samples at Real World Environment Noise
An Improved Approach for Word Ambiguity Removal

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Abstract

Word ambiguity removal is a task of removing ambiguity from a word, i.e. correct sense of word is identified from ambiguous sentences. This paper describes a model that uses Part of Speech tagger and three categories for word sense disambiguation (WSD). Human Computer Interaction is very needful to improve interactions between users and computers. For this, the Supervised and Unsupervised methods are combined. The WSD algorithm is used to find the efficient and accurate sense of a word based on domain information. The accuracy of this work is evaluated with the aim of finding best suitable domain of word.

Keywords: Human Computer Interaction, Supervised Training, Unsupervised Learning, Word Ambiguity, Word sense disambiguation.

1. INTRODUCTION

Sometimes people are facing problems in understanding correct meaning of the sentence. Since, sentence comprised of ambiguous words. In such case, correct meaning is taken by the context of the sentence. Usually, it is found in English language. In other words, we can say that context uniquely identifies meaning of the sentence. Based on this interpretation the ambiguity of word, known as lexical ambiguity is disambiguated; which is called as a process of WSD. Manual method of meaning extraction uses approach of searching words correct meaning in typical or online dictionaries which had several drawbacks.

To resolve an ambiguity in a sentence, natural language processing provides word sense disambiguation which governs a sentence in which the sense of a word or meaning is used, when the word has multiple meanings (polysemy). WSD is a process which identifies the correct sense of a word with the help of surrounding words in a sentence. The correct sense of a word is obtained from the context of the sentence. a different meaning of the single word is associated in each sentence based on the context, the remaining sentence gives us. Thus, if the word imagination appears near the word play, we can say that it is related to free_time and not related to a sport which is known as local context. Computers that read words, one at a time must use word sense disambiguation process for finding the correct meaning (sense) of a word. A disambiguation process requires a dictionary in which senses are to be specified and disambiguated. For identifying the correct sense of the word the ‘WordNet’ domain is used. A domain consists of different syntactic categories of synsets. It groups senses of the same word into uniform clusters, with the effect of reducing word polysemy in WordNet. WordNet domain provides semantic domain as a natural way to establish semantic relations among word senses. This functionality is used in creation of MySQL database. The system for disambiguation of ambiguity in a sentence aims to identify domain of intended sense of word. Basically, input provided to the system is a sentence with ambiguous words and the output is identified as domain of word.
2. LITERATURE SURVEY

For Word sense disambiguation, the first attempt effectively used by Michael E. Lesk was based on the Dictionary approach [1]. The problem with this algorithm is that, it defines context in a more complex way which is overcome by Simplified Lesk algorithm [2]. It can be effectively used with the WordNet lexical database. Such an attempt is made at Indian Institute of Technology, Bombay [3] and the results are promising. Navigili [4] had found that the right sense for a given word amounts to identifying the most “important” node among the set of graph nodes representing its senses. Ling Che Yangsen and Zhang [5] described a general framework for domain adaptation which contained instance pruning and weighting and the training instance augmentation. Agirre [6] described a thorough overview of the current WSD techniques and performance of systems on data sets, as well as a brief history of the field and some truly insightful discussions on potential developments. In [7] we find the most general and well-known attempt to utilize information in machine-readable dictionaries for WSD, that of Lesk, which computes a degree of overlap—that is, number of shared words—in definition texts of words that appear in a ten-word window of context.

3. SYSTEM MODEL

The system model has five stages:

**POS Tagger**
An English sentence with ambiguous words is given as an input to the project. From the sentence, content words are extracted and tagged by POS tagger [6, 7, 8] [22].

**Distribute Domain**
Then domains are distributed to Content words from the WordNet Domains which maintains domain distribution table [3, 4, 5] [22].

**Pick the Target Word**
The target word is selected by comparing WordNet, available domain and the domain of target word is displayed.

**Identification of Domain**
The accurate domain of the target word is identified by supervised and unsupervised training [1] [2] [22].

**Obtain Sense of Word**
The sense of target word belonging to the domain is obtained which is added to the domain distribution table i.e. the table is updated using supervised and unsupervised training [4].
4. WSD ALGORITHM

This algorithm is used in supervised and unsupervised training method and gives better performance than graph based algorithm. [13]. It has following steps:

**Step1:** Create a database which can store the words and their meanings.

**TABLE 1:** Fields Table  **TABLE 2:** General Words Table  **TABLE 3:** Meanings Table

<table>
<thead>
<tr>
<th>ID</th>
<th>field</th>
<th>ID</th>
<th>Word</th>
<th>ID</th>
<th>Word</th>
<th>FieldID</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Computer</td>
<td>70</td>
<td>is</td>
<td>441</td>
<td>diving</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>Sports</td>
<td>71</td>
<td>the</td>
<td>442</td>
<td>racing</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Medical</td>
<td>72</td>
<td>was</td>
<td>443</td>
<td>athletics</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>Engineering</td>
<td>73</td>
<td>that</td>
<td>444</td>
<td>wrestling</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>Factotum</td>
<td>74</td>
<td>on</td>
<td>445</td>
<td>boxing</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>History</td>
<td>75</td>
<td>of</td>
<td>446</td>
<td>fencing</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>Geography</td>
<td>76</td>
<td>for</td>
<td>447</td>
<td>archery</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>Games</td>
<td>77</td>
<td>where</td>
<td>448</td>
<td>fishing</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>Law</td>
<td>78</td>
<td>how</td>
<td>449</td>
<td>hunting</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>Biomedical</td>
<td>79</td>
<td>when</td>
<td>450</td>
<td>bowling</td>
<td>2</td>
</tr>
</tbody>
</table>

**FIGURE 2** System Model
The three tables are created as fields, general words and meanings. TABLE 1 shows fields table in which ID and Domain name is stored. An ID is assigned to respective domain name. TABLE 2 shows General words table in which ID and general words are stored after separation of words. TABLE 3 shows Meanings table in which ID, words and respective domain ID assigned to words are stored. A unique ID and FieldID are assigned to the word which belonging to correct domain name.

Step 2: Separate the content words from the sentence using Part -of- Speech tagging (POS) process. This process is used for identification of words as nouns, verbs, adjectives, adverbs, etc, since it is used to tag or mark the text [11]. FIGURE 3 shows tags which are used to mark the content words and their separation. The separation is done with the help of Penn Treebank Tagset of Part of Speech tagging process which is shown in FIGURE 3 and FIGURE 4.

Example:

<table>
<thead>
<tr>
<th>Tag</th>
<th>Description (Penn Treebank Tagset)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTR</td>
<td>Determiner</td>
</tr>
<tr>
<td>NN</td>
<td>Noun, Singular or mass</td>
</tr>
<tr>
<td>VBD</td>
<td>Verb, Past tense</td>
</tr>
<tr>
<td>VBG</td>
<td>Verb present participle</td>
</tr>
<tr>
<td>NNS</td>
<td>Noun, plural</td>
</tr>
</tbody>
</table>

FIGURE 3 Penn Treebank Tagset

The |DTR fisherman |VBD went |VBG to |the |NN bank |NN.|.

Fisherman (Noun) went (Verb) bank (Noun)

Target Word

FIGURE 4 Example of POS Tagger Process

Step 3: Decompose the separation of sentence into three categories as C1, C2 and C3 for finding results i.e. displaying correct domain of word. In step 3, various comparisons are performed to find correct domain of words. It is required to detect correct sense of word with the help of most suitable domain for a word using various algorithms and finally the meaning of a sentence.

FIGURE 5 Contents of Category C1, C2 and C3

Step 4: Supervised training module to check if the given category of words are properly processed or not. In step 2, if the inputted sentence domain displayed by the system is free_time. But this may be a wrong domain if the context based meaning is considered. According to the context, domain of play is Commerce. Since stock market is whose work is related to Commerce.
In this case, supervised training is required to train the system to pick the correct domain as Commerce. Let us assume that the sentence is

The play of the imagination.

The correct domain for the word play is Free_time. Since maximum count of comparison is 2 for domain free_time (ID 4). Suppose the next sentence is entered by user is

Play the drama.

Here, the domain of the word play and drama is Entertainment. Previously, the same word has domain related to free_time [10, 12]. It is shown in TABLE 4 below.

<table>
<thead>
<tr>
<th>FieldID</th>
<th>Word</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Play</td>
<td>Free_time</td>
</tr>
<tr>
<td>5</td>
<td>play</td>
<td>commerce</td>
</tr>
<tr>
<td>4</td>
<td>imagination</td>
<td>Free_time</td>
</tr>
</tbody>
</table>

TABLE 4 Domain Comparisons

**FIGURE 6** Supervised Training Flow

**Step 5:** Unsupervised learning module to auto update the database with the selected sentences and word-meaning pairs. The flow is shown in Fig. 7. If it is correct that is considered as correct domain of word (disambiguation) and this entry is updated in the database. Else, user has given the chance to input the sentence again. This flow is shown in Fig. 7. The knowledge acquisition bottleneck problem is overcome by unsupervised learning, since it is independent of manual work.
FIGURE 7 Unsupervised Learning Flow
The experimental setup is done by following steps and accuracy of Unsupervised, Supervised
and Hybrid method is evaluated using mathematical formula as

\[
\frac{\sum_{t} \text{Number of Correct terms}}{\sum_{i} \text{Number of Input}}
\]

Where, \( t \) = correct terms (Correctly disambiguated) \\
& \( i \) = input (Number of sentences)

Repeat the below steps for:

\[ i=1\ldots \text{number of sentences (n)}, \quad n=1\ldots15 \]

Where, \( i \) indicate sentence and \( n \) indicates number of sentences.

**Step 6:** Finally, display the **correct** domain of the word. The correct domain of the word for given example is Commerce.

5. RESULTS

**Stage 1: Part of Speech Tagger**
The first stage “POS Tagger” of the system model is implemented. FIGURE 9 shows the snapshot of POS Tagger process. This stage is used to separate the content words and general words like noun, verb, adjective etc. from the sentence in step1 and Classification of separated words in three categories c1, c2, and c3.
Sentence: Play the stock market.

Separation:
Play
The
Stock
Market
Match: play: play clustered under – Commerce
Match: play: play clustered under – Free_time
Match: play: play clustered under – Entertainment
Match: stock: stock clustered under – Commerce
Match: market: market clustered under - Commerce

FIGURE 9 Result of POS Tagger Process

Stage 2: Unsupervised Learning
There are five steps to process the system. When the domain of word is identified; it is checked by the system for correctness if the identified domain is correct then out of five steps only four steps are processed to get the output. This is shown in FIGURE 10 with example.

Sentence: The play of the imagination.

Step 1: Separating All Words
Word: The
Word: play
Word: of
Word: the
Word: imagination.

Step 2: Finding Matching Domain
Match – play: play
Match – play: play
Match – play: play
Match – play: play
Match – play: play
Match – imagination: imagination
Match – imagination: imagination

Step 3: Checking for Best Probable Field
Field 11 found 2 times
Field 2 found 2 times
Max Value: 9 For field ID: 69
The Domain is Free_time

Step 4: Checking for Correctness
Is this the type of the sentence at input? Y/N
The new elements with selected domains have been updated…

FIGURE 10 Result of Unsupervised Learning of Implemented System
Stage 3: Supervised Learning

In stage 3, when the domain of word is identified; it is checked by the system for correctness if the identified domain is incorrect then all five steps of system are processed to get the output. This is shown in FIGURE 11 with example.

Stage 4: Spell Checker Utility

Sometimes, the sentence entered by the user will be incorrect or correct. So, here apart from above results one additional step as spell checker utility is implemented. In stage 4, the corrections in spellings of the entered sentence are corrected using online spell checker concept which requires internet connection before executing the system. The result of this utility is shown below in FIGURE 12.
Stage 5: Final Result of the System
The system is used for determining correct domain of word. First part of this system is sentence collection. It is required by the user to enter the sentence after that sentence is separated by POS tagger. Once the sentence is separated out, it will be processed through various steps like domain distribution, supervised learning, unsupervised learning, WSD algorithm. The final result for the implemented system is shown below in TABLE 5:

<table>
<thead>
<tr>
<th>Sentence</th>
<th>Separation of Words</th>
<th>Target Word</th>
<th>Domain Identification</th>
<th>Comparison</th>
<th>Final Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Play the stock market</td>
<td>Play the stock market</td>
<td>Match – play: play Clustered under Match – stock: stock Clustered under Match – market: market Clustered under Match – play: play</td>
<td>Entertainment         Commerce                  Commerce         Commerce</td>
<td>Commerce</td>
<td></td>
</tr>
</tbody>
</table>

TABLE 5 Final Result of Implemented System

Stage 6: Results of Accuracy of the System
Firstly, the unsupervised learning, supervised learning and hybrid training accuracy is evaluated shown in TABLE 6 and FIGURE 13. Then comparison of all learning approaches are done and observed that these approaches gives 63%, 76% and 80% of accuracy respectively. Hence, the accuracy is improved using Hybrid training method shown in TABLE 7 and FIGURE 14.

<table>
<thead>
<tr>
<th>Sentence</th>
<th>Target word</th>
<th>Disambiguated</th>
<th>Correctly Disambiguated</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>66.67</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>6</td>
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<td>2</td>
<td>2</td>
<td>100</td>
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<td>7</td>
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<td>2</td>
<td>1</td>
<td>50</td>
</tr>
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<td>1</td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
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<td>1</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>11</td>
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<td>3</td>
<td>2</td>
<td>66.67</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>13</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>66.67</td>
</tr>
<tr>
<td>14</td>
<td>1</td>
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<td>Total</td>
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TABLE 6 Results of Hybrid Learning Method Accuracy of 15 Sentences
FIGURE 13 Hybrid Learning Method Accuracy

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<th>Sentence</th>
<th>Target word</th>
<th>Disambiguated</th>
<th>Correctly disambiguated</th>
<th>Supervised Accuracy (%)</th>
<th>Unsupervised Accuracy (%)</th>
<th>Hybrid Accuracy (%)</th>
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</table>

TABLE 7 Results of Comparison of Unsupervised, Supervised and Hybrid Learning
CONCLUSIONS

The system improves the self-learning process by obtaining correct sense of a sentence by resolving ambiguity from a word with full automation. The system requires correct domain of word identification from the sentence. Hence, sentence comprised of various content words like nouns, verbs, adjectives, adverb etc. Firstly, it is required to separate out content words from a sentence. By applying POS tagger process and WSD algorithm, domain is allotted to each word and each domain of word is compared to get correct domain of word. A count of comparisons is calculated, the domain which has the maximum count is assumed as correct domain. Also, this system improves the accuracy of identifying the correct domain of word. As per the Table 8 it shows that self learning language is improved by obtaining correct sense of a word by removing ambiguity from a sentence with full automation. Also, improves disambiguation process by obtaining appropriate sense of a word. The synonym relationship approach is used to identify intended domain of word. The system is trained using supervised training to check correctness of domain which gives 76% of accuracy; an unsupervised learning is used to update the database with the selected sentences and word-meaning pairs automatically. It gives 63% of accuracy. The hybrid method improves this accuracy up to 80% from Table 7. In this system, when the number of target word is correctly disambiguated system gives 100% accuracy. Else, the accuracy may be 66% or 50%. Hence, the overall 80% accuracy is evaluated. These results generated by the system are beneficial for Human Computer Interaction as it is motivating people to learn the language by themselves using computer in the absence of teacher. Additionally, the spell checker utility is implemented to avoid mistakes in words.

REFERENCES


[9] Leung (2006), "Learners as users, and users as learners", 7th International Conference on Information Technology Based Higher Education and Training, ITHET '06.


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