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Numeric Devnagari Sign Language Translator using Two Hands Single Camera Approach

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ABSTRACT

Recognition of Numeric Devnagari Sign Language (DSL) using Hand Gesture Recognition System (HGRS) has become an essential tool for hearing and speech impaired to interact with commoner's via a computer system. Our work is on the development of the proposed system Real-time Numeric Devnagari Sign Language Translator (RTNDSLT). The system architecture of RTNDSLT system is mainly comprised of five phases arranged in layered fashion from top to bottom. Vision-based, real-time and static RTNDSLT system works in cluttered background with mixed lighting conditions. This system focuses on fingertip recognition technique, Peak-and-Valley Detection algorithm, and Peak-Point Detection algorithm along with convex hull. RTNDSLT system achieves a recognition rate of 94.13% using Two Hands Single Camera approach and fingertip recognition technique.

Keywords: Devnagari Sign Language (DSL), Fingertip Recognition Technique, Two Hands Single Camera approach, Cluttered Background, Devnagari Numbers

I. INTRODUCTION

Multiple HGRS have been developed for identification of diversified sign languages using effective techniques in real-time. Real-time dynamic HGRS recognizes hand gestures from continuous hand motion for English numbers from 0-9 based on HMM. It perceives the gesture with the recognition rate of 93.84% and works in the complex background [1]. A simulator for smartboard presents gesture detection algorithm by coordinating cues from visual, speech, and electronic slides. Specifically, intentional gestures are predicted by the modified HMM. A realtime application such as simulated smartboard and the attainability check of the prediction algorithm using hand gesture and laser pen is developed. The framework acquires an accuracy of 85% with recognition time of 1.8 Seconds [2]. Real-time HGRS

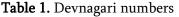
works with powerful hand tracking from depth image sequences using HMM. It obtains recognition rate of 92% in the complex background for signing digit gestures from 0 to 9 [3]. Furthermore, two realtime ASL recognizers use the desk and a wearable computer-based video respectively. Recognizer uses a single camera to track the user's unadorned hands and HMM for recognition of sentence-level continuous ASL. The first recognizer achieves 92% word accuracy and the second recognizer accomplishes 98% accuracy for 40-word lexicon [4]. HGRS uses the real-time tracking method and HMM achieves identification rate of 90% for 20 different gestures in the stationary background [5]. Gesture segmentation and recognition system present Deep Dynamic Neural Network (DDNN) for multimodal gesture recognition. A semi-supervised hierarchical dynamic framework based on HMM for simultaneous gesture achieves a recognition rate of 84.9% [6].

Real-time hand gesture detection and recognition system use bag-of-features, multiclass Support Vector Machine (SVM), K-means clustering, and skin detection in the cluttered background for object detection. It accomplishes detection rate of 96.23% with detection time of 0.017 Seconds per frame for training data set of 1000 samples [7]. Moreover, vision-based, real-time HGRS provides fast identification process of hand gesture and an effective feature extraction process. The system comprises of a Camshift algorithm, SVM, Discrete Fourier Transform (DFT), Fourier descriptor, and an outline feature with an accuracy of 93.4% [8]. Realtime HGRS identifies static hand gestures using Fourier descriptor, K-Nearest Neighbour (KNN), and SVM. It fulfils a recognition rate of 97.5% for 64 points using SVM [9].

Furthermore, the real-time and non-verbal system uses networked virtual environment technology to implement Telepresence that allows participants to interact with each other in cyberspace. The system works with computerized reasoning technique and semantic element extraction for recognition of Chinese Sign Language (CSL) and Japanese Sign Language (JSL). The system is appropriate for sign language detection with an identification rate of 84% [10]. Real-time HGRS detects ASL numbers from 0 to 9 using a single camera. The system works with HSV images, histogram, and Euclidian distance and accomplishes recognition rate of 93.1% [11]. HGRS presents a methodology using a neighbourhood search algorithm for cluster labelling and parameter estimation of the automated setup. Similarly, the system is based on Fuzzy C-Means (FCM) components and works for three databases (BGU, ASL, and Gripsee) in real-time. It achieves recognition accuracy of 98.9% and 98.2% for dependent and independent systems, respectively [12]. It is evident that many real-time HGRS have been developed for recognition of numbers based on

Single Hand Single Camera approach. However, there exists a wide scope to enhance HGRS design for recognition of Devnagari Sign Language (DSL) numbers using Two Hands Single Camera approach for speech and hearing impaired users to interact with general users.

With the potential use of technology, it has become easy to design and develop the systems as per the requirements of a variety of users including hearing and speech impaired users. In this paper, we have designed a robust and reliable Real-Time Numeric Devnagari Sign Language Translator (RTNDSLT) system. The system produces verbal output in the form of voice (for the normal users) and the text (for hearing impaired users) with respect to input as numeric DSL. Our focus lies in the execution of the system in real-time for translating DSL numbers into speech. Devnagari numbers and its corresponding DSL numbers are shown in Table I and Figure 1 respectively. Figure 2 represents the invasive DSL numbers for the purpose of experimentation. In Section II, we focus on working of RTNDSLT system. Section III highlighted mainly on algorithmic approach used in RTNDSLT system. We have presented experimental results and implementation of RTNDSLT system in Section IV. In Section V, we have discussed experimental results and analysis. Comparative performance of RTNDSLT system is described in Section VI. Finally, we conclude with conclusion in Section VII.



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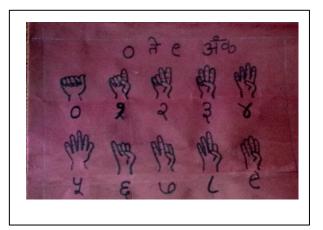


Figure 1. Devnagari Script with Corresponding DSL Numbers

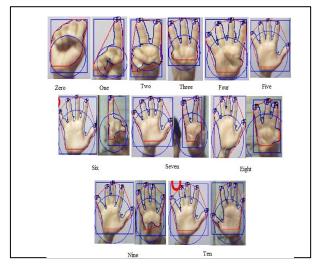


Figure 2. Invasive DSL Numbers used in Two Hands Single Camera Approach

II. WORKING OF RTNDSLT SYSTEM

We have developed, designed, and implemented real-time recognition in RTNDSLT system for DSL numbers. Further, the architecture of RTNDSLT system is presented in Figure 3 which is fragmented into five consequent phases. These phases include namely; image capturing, image pre-processing, hand tracking, image post-processing, and sound mapping. Image capturing phase deals with capturing RGB image in the form of DSL number image using the web camera and it is assumed that the background is cluttered with mixed lighting conditions. Image preprocessing phase consists of skin segmentation as well as black and white conversion process. Skin segmentation is employed to convert YCbCr image of DSL number to RGB image and RGB image to grey image. Subsequently, grey image is translated to binary image using black and white conversion process. Normalization technique is applied to the resultant binary image of DSL number. In this phase, median filter followed by Gaussian filter is applied on binary image of DSL number to remove the noise.

Hand tracking phase is comprised of morphological operations and region extraction. Morphological operations such as erosion and dilation are applied to filtered binary image of DSL number for obtaining smooth image whereas Region of Interest (ROI) is extracted using biggest BLOB of specified size in region extraction. This ROI is used as an input to the next phase of our proposed system i.e. image postprocessing. Image post-processing phase deals with recognition of Devnagari number. We discuss this phase in detail in next sub-section. Further, recognized Devnagari number is converted to speech in sound mapping phase. Now, we discuss the vital part of our methodology i.e. image post-processing Fig. 3. This phase includes Fingertip based Recognition to enhance the performance and may be used alternately. And, the system is implemented using algorithms such as Peak-and-Valley Detection, and Peak-Point Detection algorithm. We discuss fingertip based recognition and these algorithms in subsequent sections.

A. Fingertip based Recognition Method

Fingertip based recognition method locates open finger peak points in detecting hand region. In this phase, we extract hand contour from extracted hand where a hand contour is series of edge points of hand object. We need to determine fingertips in hand contour at the stage. Fingertips may be defined as points at the end of a smooth hand contour as shown in Figure 4 and fingertip based recognition for DSL numbers is as depicted in Figure 5.

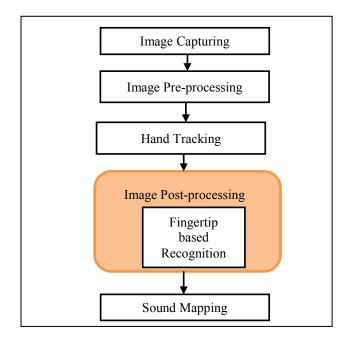


Figure 3. Architecture of RTNDSLT System

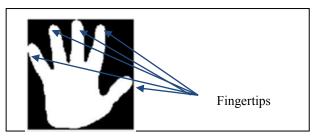


Figure 4. Fingertips in Hand Imag

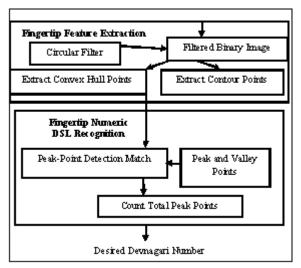


Figure 5. Fingertip based Recognition for DSL Numbers

Implementation of the fingertip based recognition method is related to the construction of sample image dataset and input hand image of numeric DSL. This method deals with sample image dataset and fingertip based recognition. Here, we extract fingertips and store in the sample image dataset. At the same time, fingertip based recognition may be further divided into two sub-phases namely; fingertip feature extraction and fingertip numeric DSL recognition and are discussed subsequently.

During fingertip feature extraction, the input hand image is filtered by the use of two-dimensional circular filter. The filter plays an important role in smoothing the corners of a binary image. We extract convex hull points and contour points from the filtered binary hand image. For a nonempty set of points in a plane, the convex hull is the smallest convex polygon that covers all the points in the provided set. At this stage, we create contour set of filtered hand image. The contour set of an object contains boundary (i.e. edge) points. Thus, we have developed two feature sets of an image namely; convex hull set and contour points set. Further, fingertip numeric DSL recognition sub-phase is initiated with the peak-point detection match. Convex hull set, contour points set, and peak and valley points act as input for peak-point detection match. Using this match, we may find each curve point from contour set include namely; peak and valley points. Accordingly, we discuss image contour finding and convex hull in subsequent sections.

Contour Finding Method

A contour is a sequence of points that are the boundary pixels of a region. Contour finding does not trace the whole pixels in an area whereas it visits only boundary pixels. Use of this technique leads to lower computation cost and the contour information that we require in decision making for fingertip detection. The contour finding method is initiated with a start point. Locating a start point may be done by scanning each row of pixels from the bottom left corner. Here, the scan of each row starts from the leftmost pixel proceeding to the right. When a white pixel is encountered, we declare that pixel as start pixel. When contour search is finished, it indicates that a hand contour is found from a smooth hand image of DSL number. A hand region and a hand contour may be plotted on RGB input image of DSL number as shown in Figure 6. A rectangle denotes the hand region and it is a boundary box of extracted hand. A contour is denoted by the boundary edge of extracted hand. Hand boundary box size is the criteria to decide whether valid input or not. In our experiment, the hand boundary box size is defined as 30 pixels in width and

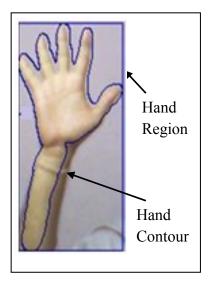


Figure 6. Hand Region and Contour of Hand Image 60 pixels in height. If any input hand image violates the boundary box criterion, it does not process further. Thus, we calculate convex hull and is discussed in subsequent section.

Convex Hull

We calculate the convex hull of the forearm contour in order to find the desired information. Mostly, the arm part is a smooth contour and contains important information however, it is not sufficient. The hand may contain more convex contours with the desired information. We need to explain the concept of convex polygon that is used in the convex hull. A convex polygon is a polygon that does not contain any concave part. Figure 7 (a) shows a concave part of a polygon by an arrow. The convex hull of the set of points is the smallest convex polygon that covers all the points in the set as depicted in Figure 7 (b). The hexagon in the Figure 7 (b) is the convex hull of the set of ten points. The six points used to compose the hexagon are called "hull points". These points are used to generate the convex hull of the hand region as shown in Figure 8. By observing the contour and its convex hull, we notice that some areas are contained in convex hull and not in the contour, are called the convexity defects. Convexity defects provide useful information about the shape of a contour.

Contour and convex hull are used in identification of peaks and valleys in hand contour. Contour points are traversed linearly with the use of three points such as X, X1, and X2, the angle between the lines as θ is computed and compared with threshold (i.e. $\theta \leq 90^{\circ}$) and detected peak and valley points set is returned as output. Peaks and valleys may be detected in a Contour Plot using Peak-and-Valley Detection algorithm (Algorithm 5.3) and Counter Plot (CP) of any image is as shown in Figure 9. After the execution of Peak-and-Valley Detection algorithm, the

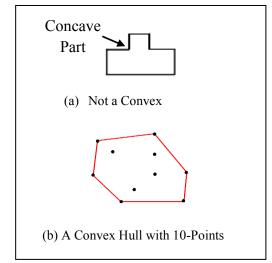
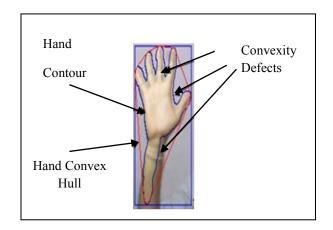
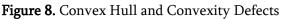
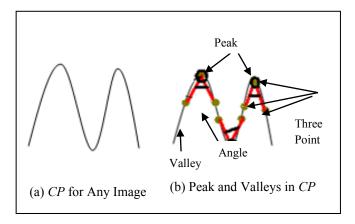
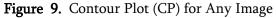


Figure 7. Image Convex Hull









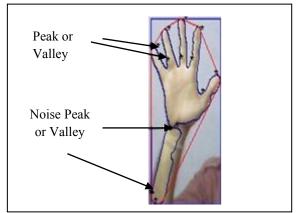
identified peak and valley points in hand contour are denoted by a star (*) symbol as depicted in Figure 10. Out of these points, some peaks or valleys may be valid or noisy. The existence of the curve at the bottom of hand contour shows the noise peak or valley as depicted in Figure11. Let us consider H as the hand region boundary box and is as represented in eq. 1. To prevent from noise points at the bottom, the biggest hand region image is cropped with size S, as represented in eq. 2.

$$H = [x, y, w, h]$$
 ... (1)

$$S = [0,0, (x + w), (y + h - 10)] \qquad \dots \qquad (2)$$

where, (x, y) denotes the location of H in the two dimensional image matrix, w and h are width and height of H respectively.

Now, cropped input image of DSL number is provided as input for convex hull and contour finding process. The bottom may be eliminated from the hand region by eliminating the noise as shown in Figure 11.



AND A

Figure 11. Bottom of Hand Contour

Peak and valley point set consists of peak and valley points. This set does not differentiate between peak and valley in general. Thus, we need a mechanism that may discriminate peaks and valleys for recognition of fingertips. Using Peak-Point Detection algorithm (Algorithm 5.4), it is easier to extract peak point set from peak and valley point set. The peak point set is a subset of peak and valley point set. The peak point represents an open finger (or thumb). An open finger is a part of the numeric DSL gesture. To select noise free peak points from the peak and valley points, we define two important decision rules namely; enclosed circle point elimination and cross threshold distance point elimination. The enclosed circle point elimination rule predicts the noise free peak or valley points using circle strategy. Let us consider a circle C with radius R and center P, and assume a hand boundary box with the width w. All the points outside the perimeter of a circle C are considered as a useful peak or valley points and R and P as represented in eq. 3 and eq.4 respectively.

$$R = \frac{w}{2} \qquad \dots \qquad (3)$$

$$P = CM \qquad \dots \qquad (4)$$

where, CM denotes centroid. The distance D between two points A and B may be calculated using Euclidean Distance (ED) between A and B by using eq. 5.

$$D(A, B) = ED(A, B)$$
 ... (5)

Figure 10. Peak and Valley Points in Hand Contour

III. ALGORITHMIC APPROACH USED

We have devised a RTNDSLT system for recognition of DSL numbers in cluttered background with mixed lighting conditions. Inputs to this system are running image (i.e. input binary image) and training dataset images. Fingertip based recognition method is applied simultaneously on two inputs namely; running image and training dataset images. We have established diversified algorithms such as Peak-and-Valley Detection and Peak-Point Detection along with Sample-Image-Database algorithm and are briefly discussed in subsequent sections.

A. Peak-and-Valley Detection Algorithm

We present firstly the informal description of Peakand-Valley Detection algorithm i.e. Algorithm 1, followed by its formal description as follows:

a. Informal Description

We present now the informal description of aforesaid algorithm in this section. In Peak-and-Valley Detection algorithm, a non-empty set of hand contour points, C is an input and D is the detected peak and valley points set is the output. Firstly, we initialize peak and valley set D as empty set, index k as 1 for counter set, and index j as 0 for peak and valley set as zero. Further, the complete contour set is traversed and includes calculation of 16 points distance store in different variables such as u and v. Further, we calculate $\cos Angle using \cos \theta$ angle at point located at (k+16)th location. At the same time, cosAngle is computed using function dotProduct that is employed to find dot product between u and v. Furthermore, an angle in degrees is determined by applying inverse of the cos operation on cosAngle to generate angle in degrees i.e. degreeAngle θ . In our algorithm, contour points C are traversed linearly with the use of a pair of three points, the angle of a point is computed and compared with threshold and detected peak and detected peak and valley points set D is returned as output.

b. Formal Description

Algorithm 1: Peak-and-Valley Detection Algorithm for RTNDSLT System

//* Here, C is non-empty set of hand contour points
 and D is peak and valley points set *//

begin {Main} //* Algorithm begins *//

j = 0;

Step IV: //* traverses complete contour set *//
while (C(k) ≠ null)
begin

//* calculates the vector 16 points distance for u and v *//

$$u = C(k+16) - C(k);$$

$$v = C(k + 16) - C(k + 32);$$

//* calculates cos θ angle at point located at (k+16)th location *// cosAngle= dotProduct (u, v)/ (|u| |v|); degreeAngle= cos⁻¹(cosAngle) ;//*computes angle in degree *//

if (degreeAngle <= 90) //* compares an angle with threshold *//

begin

//* finds next location for assigning
peak or valley point *//

j = j + 1;

D (j) = C(k +16); //* assigns peak or valley point contour set *//

//* shifts k point in contour *//
k = k + 32 + 1;
else

end if

end while return D; //* detects the peak and valley points set as output *//

end. **{Main}** //* Algorithm ends*//

B. Peak-and-Valley Detection Algorithm

We present firstly the informal description of Peak-Point Detection algorithm i.e. Algorithm 2, followed by its formal description as follows:

a. Informal Description

We present now the informal description of Peak-Point Detection algorithm in this section. In Peak-Point Detection algorithm, various inputs are used such as A Peak and Valley (APV) point set, the width (w) of the hand region boundary box, a non-empty set of Convex Hull (CH) point of hand, Revised centroid i.e. Center of Mass (CM) of convex hull, and displaced centroid CM(1) in x and CM(2) in y directions and output is a set of Peak Points (PP). Here, we compute revised centroid CM using displaced centroids CM(1) in x direction and CM(2) displaced by 20 points in y direction. Further, we calculate radius r by applying half of hand region boundary box width w. We initialize peak point set PP with the empty set and index i as 0 for peak point set since it is empty along with index k as 1 for convex hull set and traverse it till size (CH) value. At the same time, the complete peak and valley point set is visited that includes a calculation of the size of APV. Furthermore, we evaluate the Euclidean distance between convex hull centroid and APV and it is stored in distance D1. Here, D1 uses enclosed circle point elimination for checking the existence of points outside the circle of radius r. Similarly, we determine the Euclidean distance between convex hull CH and APV and it is stored in distance D2. Here, D2 is applied to check the distance with threshold T using threshold distance point elimination. Consequently, existence of peak point PP in APV and it assigns the original peak points of peak and valley set to peak point set. And, the detected set of original peak points is returned as output. The total number of peak points of the fingers is employed in detecting desired Devnagari number.

b. Formal Description

We present now the formal description of Peak-Point Detection algorithm in this section.

Algorithm 2: Peak-Point Detection Algorithm for RTNDSLT System

//* Let APV be a peak and valley point set, w be the width of the hand region boundary box, CH be a non-empty set of convex hull point of hand, and CM be a revised centroid or Center of Mass of convex hull, CM (1) and CM (2) are displaced centroid in x and y directions respectively are the inputs and output is a set of Peak Points, PP. *//

begin {Main} //* Algorithm begins*//

```
Step I: //* computes revised centroid *//
        CM = [CM(1), CM(2)+20];
Step II: //* calculates radius (r) *//
         r = w/2;
Step III: //* initializes peak point set PP with
           empty set *//
         PP = \emptyset;
Step IV: //* initializes index i as zero since it is
          empty *//
         i =0;
Step V: //* initializes index k for convex hull set
          and traverse it *//
       for (k = 1 \text{ to size}(CH))
         begin
         for ( index =1 to size(APV)) //* visits
           each peak and valley point *//
         //*
               computes
                             Euclidean
                                           distance
          between centroid and APV *//
                    EuclideanDistance
                                              (CM,
         D_{1=}
          APV(index);
```

```
if (D_1>r) //* uses enclosed circle point
          elimination *//
         begin
        //*computes
                          Euclidean
                                         distance
         between CH and APV *//
         D_2
               =
                   EuclideanDistance
                                         (CH(k),
         APV(index));
                        //* checks distance with
        if (D_2 < T)
         Threshold (T) *//
         begin
         if (! exist(PP, APV(index))) //* checks
         existence of peak point *//
           begin
          i = i+1;
          //* assigns original peak point of APV
         set to PP set *//
          PP(i) = APV(index);
          end if
         end if
       end if
      end for
    return PP;
                    //* the set of original peak
points as output *//
```

end. {Main} //* Algorithm ends*//

C. Sample-Image-Database Algorithm

We present firstly the informal description of Sample-Image-Database algorithm i.e. Algorithm 3, followed by its formal description as follows:

a. Informal Description

In our algorithm, RGB image sequences and database path are the inputs and output is sample image database (i.e. training dataset). Here, getFrame() function is used to grab the first frame from sequence video and stored in frame. Further, frame is iterated until complete video sequences are processed. At the same time, skinSegmenation() function is applied to frame for skin color filtering and stored in skinFrame as noise free frame. And, filtering is followed by morphological operations applied on skinFrame using function morphologicalImageProcessing() and resultant frame is stored in noisefreeFrame. The hand detection process is applied on noisefreeFrame using handDetection() function and stored in handFrame. Similarly, the hand image denoted by handImage is cropped from handFrame using cropHand() function. Also, the handImage is stored along with DatabasePath. Furthermore, we extract the next sequence of video by using getNextFrame() function and stored in frame. The whole procedure is repeated and consequent frames are extracted till the video is running and it is applied in the construction of the sample database. Sample database (i.e. training dataset) is employed to store DSL numbers ranging from 0 to 10.

b. Formal Description

We present now the formal description of Sample-Image-Database algorithm in this section.

Algorithm 3: Sample-Image-Database Algorithm

//* Here, RGB image sequences and database path are the inputs and output is sample image database (i.e. training dataset). *//

begin {Main} //* Algorithm begins*//

Step I: //* grabs the first frame from sequence video *//

frame=getFrame(video);

Step II: //* iterates until complete video sequences are processed *//

while(frame!=null)

begin

skinFrame=skinSegmenation(frame);
//* skin color filtering *//

//* removes noise and applies
morphological operations *//

noisefreeFrame=morphologicalImageProcessing(
skinFrame);

handFrame=handDetection(noisefreeFrame);
//* detects hand *//

handImage=cropHand(handFrame);
//* crops only hand image *//

store(DatabasePath, handImage); //*stores hand image along with database path *//

frame=getNextFrame(video); //*extracts
next sequence *//

end while //* forms sample database *//

end {Main} //* Algorithm ends*//

IV. EXPERIMENTAL SETUP AND IMPLEMENTATION

In our experimentation, there exist some hardware requirements. and software The hardware requirements include processor 3.06 GHz, RAM 1 GB, web camera of resolution 10 Mega Pixel, web camera frame rate 30 Frames/ Sec. On the other hand, software requirements cover Windows XP, MATLAB 2012, and web camera driver. The web camera and light source must be located in front of the user. We have implemented RTNDSLT system using five phases of architecture such as image capturing, image pre-processing, hand tracking, image-post processing, and sound mapping.

a. Implementation Of Pre-Requisite Phases

In image capturing phase, the system parameters and resources are initialized. Basically, this phase is profoundly concerned with appropriate installation of web camera and capturing of images of numeric DSL. The web camera must be placed in front of user and captures RGB image in the form of a numeric DSL image. Images of numeric DSL are captured in RGB color format with the frame size of [320*240] pixels in cluttered background along with mixed lighting conditions. Configuration of camera deals with the initialization of parameters such as high brightness (145-175 Lumens), frame rate (30 Frames/ Sec) and frame interval (1 or 3). Thus, the captured images will be in the form of digital frames. Every first (or third) frame is extracted from the input image frame buffer and finally RGB image will be produced as an output.

The RGB image captured in previous phase acts as input to image pre-processing phase. It consists of two main sub-tasks namely; skin segmentation and black and white conversion process. Skin segmentation process is performed using the MATLAB function rgb2ycbcr that converts RGB image into YCbCr color format. Here, Y stands for the luminance component; Cb and Cr are the bluedifference and red-difference chrominance components respectively. In YCbCr image, chrominance pixels ranges are used for skin pixel detection whereas luminance is not used in skin segmentation. If YCbCr image pixels lie within the defined ranges of chrominance, the pixels are considered to be skin color pixels. The remaining pixels are assigned as black color values that are used for background subtraction. Further, the non-pixel values are set to black and skin pixel values are assigned as the white pixel values in black and white conversion process.

Hand tracking phase is the most important phase of RTNDSLT architecture. The input to this phase is black and white image that may contain noise. Hand tracking phase deals with performing the sub-tasks such as morphological operation and Binary Linked (BLOB) extraction. In morphological Object operation, some of the pixels may be lost in black and white image. The noisy input image is always rough and cannot be used for any meaningful decision. To recover the lost pixels and to smoothen the image, some logical operations such as erosion and dilation are applied. These processes are executed by introducing four pixels in width and seventy five pixels in height in each line. At this stage, the holes filling process is applied with four pixel connectivity in the image. Smooth and noise free image obtained is a new embedded version of the image. Further, the biggest BLOB extraction is used for detection and

tracking of hand object in the human image. The noise free image obtained after morphological operation, acts as the input in this phase. The input image contains sub-images as regions and these regions are labeled with a use of eight pixel connectivity. We have calculated the area of each labeled region as area set and selected the largest area from area set. This selected largest region is set as true value (white pixel) and other remaining regions are set to be false as a value (black pixel). At this stage, the image contains only the biggest region and may be called as a BLOB. This BLOB represents the only hand in the human image.

b. Implementation Of Image Post-Processing Phase

The prime focus of post-processing phase is the recognition of numeric DSL with low execution time and higher recognition success rate. This phase may be accomplished using Fingertip Recognition to enhance the performance. Accordingly, the system is designed, developed, and implemented using Peakand-Valley Detection (Algorithm 1), and Peak-Point Detection (Algorithm 2) algorithm. These algorithms are used to offer recognized Devnagari numbers. While using these algorithms for recognition of eleven DSL numbers, our input is a filtered (smooth) one handed (i.e. 0 to 5) and two handed (i.e. 6 to 10) images of DSL numbers with size [320*240] pixels. In the first step, hand region crops from the input image and then cropped hand image of DSL number is resized with [M*N] pixels (same as sample image resized before feature extraction).

Sound mapping phase is used to generate sound in respect of recognized Devnagari number. Audio signal processing is required to produce the sound by the speaker. We have developed a wave library that consists of wave files for each Devnagari number (i.e. from 0 to 10) in RTNDSLT system. At this stage, these recorded wave files are used to produce sound (digital audio). In digital audio, the most commonly used audio sampling rates are 44.1 kHz, 48 kHz, 88.2 kHz, 96 kHz, and 192 kHz. It has been observed that lower sampling rates are beneficial for small data size and easier storage and transport. According to Nyquist-Shannon theorem, sampling rates higher than 60 kHz may not supply more usable information for human listeners. The Audio Engineering Society recommends 48 kHz sample rate for most applications. On the other hand, it suggests 44.1 kHz for Compact Discs (CDs) and other consumer uses. In our experimentation, we have used the audio sampling rate at 11025 Hz in our recording function. It may be observed that sampling rate of 11025 Hz is one quarter of the sampling rate of audio CDs. It is used for MPEG audio and for audio analysis of subwoofer band passes. Here, we have loaded the wave library and sent the audio signals to the speaker for generating sound for numeric DSL.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Real-Time Numeric Devnagari Sign Language Translator (RTNDSLT) system is devised for translation of 11 DSL numbers into verbal output in the form of voice. It is mainly concerned with the detection of DSL numbers using Two Hands Single Camera in cluttered background with mixed lighting conditions. The architecture of RTNDSLT system is fragmented into five consequent phases namely; image capturing, image pre-processing, hand tracking, image post-processing, and sound mapping. Image capturing phase deals with capturing RGB in the form of a DSL number image. In image postprocessing phase, RGB image is converted to YCbCr MATLAB function rgb2ycbcr image and subsequently YCbCr image converted to binary image. At the same time, noise is removed from binary image using median filter followed by Gaussian filter. Noise free binary image acts as input to hand tracking phase. This phase deals with morphological operations such as erosion and dilation applied on noise free binary image to obtain a smooth binary image. The biggest BLOB of size [M*N] pixels is extracted from a smooth binary image using a program code for Biggest BLOB Extraction. Extracted BLOB acts as input to image postprocessing phase. The prime focus of post-processing phase is the recognition of numeric DSL with low execution time and higher recognition success rate.

Therefore, we have designed, developed and implemented RTNDSLT system using fingertip based recognition. At the same time, we have established algorithms such as Peak-and-Valley Detection (Algorithm 1), and Peak-Point Detection (Algorithm 2) algorithm. Moreover, we have applied on Sample-Image-Database (Algorithm 3) algorithm used for storage of images in the training dataset. Training dataset required for implementation of fingertip based recognition method is constructed using a program for Fingertip Knowledge Dataset is used to generate training dataset for fingertip based recognition method. Moreover, training dataset is constructed using Sample-Image-Database algorithm (Algorithm 3). We have constructed training dataset of size 1100 samples using this algorithm. In this context, we present sample image database for one hand image samples for five digits is as shown in Figure 12 ranging from one to five as depicted in Figure 12 (a) to Figure 12 (e) respectively. Further, minimum Euclidean distance between training dataset images feature vectors and running image (i.e. extracted BLOB) feature vector is calculated. Least Euclidean distance is used to recognize the best suitable pattern as Devnagari number. Lastly, sound mapping phase is applied to convert Devnagari number (i.e. text) to speech using audio files.

Consequently, we have evaluated experimental results of our RTNDSLT system in real-time using fingertip based recognition method. Accordingly, recognition rate achieved by RTNDSLT system using fingertip based methods is presented in Table 2. It is observed that RTNDSLT system achieves a recognition rate of that recognition rate is 94.13% using the fingertip based recognition method. Here, recognition of DSL numbers and corresponding Devnagari number using fingertip based method act as outcome of RTNDSLT system. The outcome using aforesaid BOF methods is represented in Figure 13.

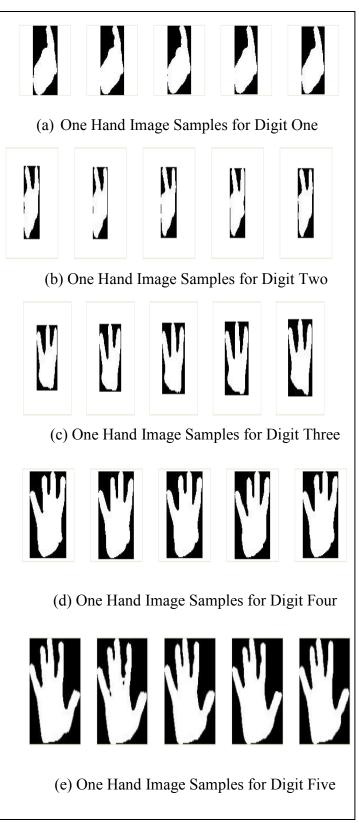


Figure 12. One Hand Image

DSL Number	Fingertip Recognition Method		
DSL Number			
0	95.61%		
1	91.59%		
2	95.59%		
3	96.59%		
4	94.63%		
5	96.64%		
6	92.89%		
7	94.16%		
8	95.44%		
9	90.11%		
10	92.23%		
Average Recognition Rate (%)	94.13%		
Rate (%)			

Table 2. recognition rate of rtndslt system using fingertip recognition method

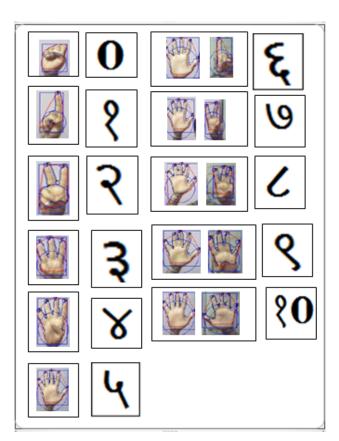


Figure 13. Outcome of RTNDSLT System as Recognition of DSL Numbers and Corresponding Devnagari Numbers using Fingertip based Recognition Method

VI. COMPARATIVE PERFORMANCE OF RTNDSLT SYSTEM

We now present the comparative performance of RTNDSLT system with other HGRSs used for recognition of DSL numbers. On the basis of some vital factors such as approaches, techniques, background, and recognition rate, a comparative performance is presented as shown in Table III. Following are the important observations associated with the execution of RTNDSLT system:

As compared to existing HGRSs, RTNDSLT system recognizes 11 DSL numbers from 0 to 10 using the fingertip recognition method. It attains the recognition rate of 94.13% using Two Hands Single Camera approach in the cluttered background.

- ✓ Numeric HGRS is designed for identification of DSL numerals using histogram and skin color segmentation techniques, accomplishes the detection rate of 93.1% including mixed lighting conditions in the static background.
- ✓ HGRS_TM is developed to recognize 10 DSL numbers using template matching, acquires the detection rate of 90.1% using Single Hand Single Camera approach in the static background.
- ✓ HGRS_FT is designed for detection of DSL numbers using FT, achieves a recognition rate of 89% using Single Hand Single Camera approach in static background.
- ✓ Using EOH in HGRS_EOH, DSL numbers are recognized with the recognition rate of 86.2 % along with Single Hand Single Camera approach in the complex background has been reported.
- ✓ HGRS_DCT is devised using DCT technique to detect DSL numbers and acquires the lowest detection rate of 82.2% using Single Hand Single Camera approach in the complex background.
- ✓ Finally, it has been observed that RTNDSLT_Centroid and RTNDSLT_Hist is implemented using centroid and histogram

recognition techniques for identification of 11 DSL numbers accomplishes the lowest recognition rate of 58.88% and 43.3% respectively in cluttered background using Two Hands Single Camera approach.

However, it is evident from Table III that highlighted the performance of RTNDSLT system shows effective outcome as compared to other HGRSs for identification of DSL numbers.

HGRS	Approach Used	Technique Implemented	Background	Recognition Rate
Numeric HGRS	Single Hand Single Camera	Histogram	Static	93.1%
HGRS_DCT	Single Hand Single Camera	Discrete Cosine Transform	Complex	82.2%
HGRS_FT	Single Hand Single Camera	Fourier Transform	Complex	89%
HGRS_EOH	Single Hand Single Camera	Edge Orientation Histogram	Static	86.2%
HGRS_TM	Single Hand Two Camera	Template Matching	Static	90.1%
RTNDSLT_Hist	Two Hands Single Camera	Histogram based Recognition Method	Cluttered	43.3%
RTNDSLT_Centroid	Two Hands Single Camera	Centroid based Recognition Method	Cluttered	58.88%
RTNDSLT_Fingertip	Two Hands Single Camera	Fingertip based Recognition Method	Cluttered	94.13%

Table 3. Comparative Performance of HGRSs andRTNDSLT system

VII. CONCLUSION

Auditory handicapped users normally make use of sign language for communication purpose. In order for an ordinary person to communicate with deaf people, we have devised Real-time Numeric Devnagari Sign Language Translator (RTNDSLT) system. It mainly deals with the detection of DSL numbers using Two Hands Single Camera approach in cluttered background. The architecture of RTNDSLT system is fragmented into five consequent phases namely; image capturing, image preprocessing, hand tracking, image post-processing, and sound mapping. We have introduced fingertip based recognition method in image post-processing phase to enhance the performance of system in realtime. Further, we have implemented a system using fingertip based recognition algorithms such as Peakand-Valley Detection, and Peak-Point Detection algorithm. Two handed DSL number images and sample database images are the inputs provided to RTNDSLT system. Here, DSL number images captured using web camera of resolution 10 Mega Pixels at a distance of 1 meter from camera with mixed lighting condition. These captured images are stored in training dataset using Sample-Image-Database algorithm and forms training dataset of size 1100. The system identifies 11 DSL numbers and accomplishes the recognition rate of 94.13% using fingertip based recognition method with recognition time of 0.03 seconds.

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