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Integrative Review on Vision-Based Dynamic Indian Sign Language Recognition Systems

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***Abstract*—Human-computer interaction is capable of solving the complex problems and challenges faced by human beings, among many of the complex jobs Sign Language Recognition is one of them. Therefore, automatically detecting the sign language is a broad area of research many works have been done in this area, and still, the work is going on. A variety of sign languages can be found throughout the globe sometimes the sign languages can be diversified by the country or region, the sign language(SL) which is available in India is known as the Indian Sign Language(ISL). Indian sign language requires the involvement of both hands, face, and upper body part movement which makes it difficult from the other single-handed sign languages. If we compare the Static gesture identification with the dynamic gesture identification, it's obvious that the former is easier. In real-life scenarios, a system should have the ability to identify the continuous and dynamic gestures, so that it can become an interface between the hearing impaired people and the normal people. Therefore, an Integrative review has been presented here which strongly summarizes the works on Indian Sign Language Recognition(ISLR) systems capable of identifying the dynamic and continuous Vision-based gestures without using any gloves or sensor-enabled wearables.**

Keywords—Indian Sign Language, Support Vector Machine, Neural Network, K-Nearest Neighbor Classification, Euclidean Distance

I. Introduction

Every form of gestural has its predefined pattern and meaning which can be used to transmit the messages to do the conversation and this form of conversation is known as Sign Language(SL). It can include a single hand, double hand, fingers, arms, and a combination of them which is widely used by the hard-of-hearing peoples for regular communication. Literature survey reports that there are radiated SL available throughout the globe, the SL which is available and used within India is acknowledged as the Indian Sign Language(ISL) [1]. According to the 2011 census India has around 50lakh peoples who are deaf therefore the ISL became one of their Human Rights in India according to RPwD (Rights of Persons with Disabilities) Act 2016.

Sign Language Recognition(SLR) System can be categorized into two categories: Gloves/Sensor-Based and Vision-Based. In real-life scenarios, the former one may not be very efficient because this type of recognition system includes some kind of wearables such as hand gloves which need to be used during the communications which may create hesitation among the signers, while on the contrary, the latter one does not require any of the wearables it is based on the Image Processing Techniques so any device capable of capturing the images can be utilized with the SLR systems for recognition. Which may be convenient for the signer to use. Therefore, in this paper, we have reviewed only those works which are based on Indian Sign Language Recognition(ISLR) and uses the Vision-based inputs for recognition and can identify the continuous gestures inputs.

Every SL system includes 5 major steps such as 1- Data acquisition: in this step gesture images are captured to train the models, 2- Pre-processing: Raw images are converted to specific formats as per the models need, 3- Segmentation: important portions of the images which are required for SL are retrieved, 4- Feature Extraction: after recognizing the required segments from the image, feature matrices are prepared, and finally 5- Classification: Final step which recognizes the gestures.

In this review paper, the focus has been given to the classification techniques that have been used by the researchers, and research works have been categorized according to the classification techniques in a chronologically ascending manner, comparison has been made on the Segmentation, Feature Extraction, and classification techniques used by the researchers and the level of accuracy, that has been achieved by them.

The paper has been orchestrated as follows: Section II holds an overview of the basic architecture of the SLR Systems followed by Section III which summarizes the various ISLR systems available in the literature, and the Proposed Methodology can be found in Section IV, finally, the conclusions and future works have been discussed in Section V.

II. ISL Recognition System Architecture

SL systems architecture consists of a few basic steps represented in "Fig. 1" which are followed by almost every SLR system and the basic step involves Data Acquisition, Segmentation, Feature Extraction, and Classification. This section will explain each of these steps in details as below

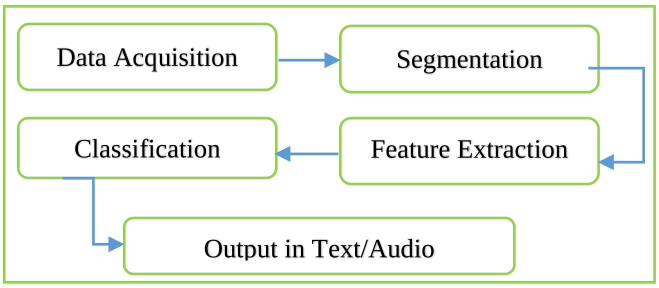

Fig. 1. Sign Language Recognition System Architecture

A. Data Acquisition:

Data acquisition in vision-based SLR systems is done through image capturing devices like Leap Motion Camera (LMC), Kinect, Mobile Phones having a camera, or any device that is capable of capturing the images and videos. The gestures have been collected using these devices and forwarded to the SLR systems for its recognition and further processing.

B. Segmentation:

Segmentation is the process of segmenting the Region of Interest (ROI) from other parts of the input images, the extracted ROI is related to the gestures which can be used to train the model for differentiating the gestures from other contents of the image, this can be performed using various technologies such as YCbCr, Hue-Saturation-Value(HSV), Edge Detection, Canny Edge Detector, etc.

C. Feature Extraction:

Feature Extraction is the most crucial step in SLR because the SL model processes the feature vectors retrieved from this pace, hence the feature extraction mechanism demands to be selected carefully so that the features can be extracted irrespective of orientation, position, and illumination. There are diverse feature extraction techniques applied by the authors such as Euclidian distance, Histogram of Oriented Gradients (HOG), Optimum Feature and Bayes Classifier and 2D CNN, etc.

D. Classification:

Classification or the ISL prediction is the step that is responsible for the recognition of the input gestures and the accuracy of the system depends on this step. This step includes a model which is trained previously using the training gesture datasets, the model takes the input images and identifies the gesture which is next converted to text or speech. Several classification methods are available such as Multilayer Perceptron(MLP) Neural Network, SVM, Artificial Neural Network (ANN), Adaptive Motionlet Kernels, Euclidean Distance, Genetic Algorithm, etc.

E. Output:

After classification has been performed the results are mapped with the required labels and next the results have been converted to the required output format (text or audio) so that the user can consume it.

III. ISLR System Review

This section demonstrates the various ISLR systems which are already been implemented or suggested by the researchers, the section groups the systems according to the Classification techniques used by different SLR systems in chronological order which is believed to be helpful for the readers.

A. Support Vector Machine(SVM)

In [1] authors have proposed an approach in which they have used skin color model reference of YCbCr for segmentation, and Principle Curvature Based Region (PCBR) detector along with Wavelet Packet Decomposition (WPD-2) used for feature extraction. An accuracy of 91.3% has been achieved by using Multi-Class Non-Linear SVM.

In [2] authors have achieved by employing the global thresholding algorithm for the segmentation process and Structural Shape Descriptors have been introduced to do the feature extraction whereas Solidity, Orientation, Aspect ratio, Elongation, Compactness have been used as the shape descriptors. finally, Multi-Class SVM (MSVM) has been enforced for the classification of 60 different gestures resulting in 96% accuracy.

In [3] authors have been used the HSV mechanism for doing the segmentation and Spatial domain method along with the Kalman Filter used for feature extraction, the Multi-class SVM has been deployed for the classification of 4 gestures which has given the accuracy of 97.50%.

Simple edge detection techniques are used by authors in [4] for segmentation followed by Krawtchouk Moment and Correlation-Based Feature Selection (CFS) algorithm to perform the feature extraction. In this paper, the authors have used SVM PUK (Pearson VIII Universal Kernel) for the categorization of 26 gestures and have reached an accuracy of 97.90%.

Authors have used YCbCr color space for segmentation in [5] and Histogram of Oriented Gradients (HOG) has been used for feature extraction followed by a Multi-class SVM for classification. Here the authors have not disclosed the accuracy that has been achieved.

In [6] authors have used K-mean clustering along with the Manhattan distance mechanism for the segmentation process and 3 feature extraction methodologies such as Speeded-Up Robust Feature (SURF), HOG, and Local Binary Patterns (LBP) are utilized for extracting the required features for recognition and in the end, a model trained using the SVM is employed for the recognition which gives an accuracy of 71.85% for identifying 140 types of gestures.

B. Genetic Algorithm

Authors in [7] have proposed to use HSV color model along with the Camshaft method for segmentation and Hausdorff Distance, Fourier descriptors for feature extraction, whereas the Genetic Algorithm is been used for the classification, though the accuracy of the classification is not mentioned the authors have claimed it to be effective for ISL recognition.

C. Fuzzy Inference System

Authors in [8] have used a Discrete Wavelet Transform (DWT) infusion with Canny Edge Detector for finding out the unambiguous edges during the segmentation process and Fourier Descriptors has been used for the feature extraction, finally, Sugeno type Fuzzy Inference System is used for the classification which gives an accuracy of 96%.

D. Euclidean Distance

In [9] authors have applied Microsoft Kinects 3Gear Technologies along with the B-Spline Curve for segmentation and for feature extraction they have considered the global and local features available in a sign and pulled out the required features. For global feature extraction Axis of List Inertia (ALI) has been used on the other hand Principal Component Analysis (PCA) has been used for local feature extraction. Euclidean Distance method is used for classification giving an accuracy of 40% while testing with the images having average complexity whereas the accuracy is claimed to be 100% for the best case.

Authors in [10] have used HSV along with Histogram Matching for the segmentation process and the features of the images are extracted using the Eigenvalue and Eigenvector, finally, the classification is done by calculating the Euclidean Distance between the Eigenvector of the test picture with the database image. This approach results in 96.25% accuracy for classifying 24 signs.

In [11] an ISL Recognition Model is developed which uses HSV and Median Filter for performing the segmentation, Orientation Histogram along with Principal Component Analysis (PCA) has been used for feature extraction, this model is designed to recognize the Indian sign language sentences dynamically which achieved an accuracy of 93% for recognizing the sentences.

Canny Edge Detection along with the YCbCr mechanism has been used in [12] for doing the segmentation and the Fourier Descriptors method is used for the feature extraction and preparation of the codebook during the training session and finally, the Euclidean Distance method is used for classification which results in 97.50% accuracy.

E. Neural Network

A Deep Learning-based approach has been adopted by authors in [13] for ISL recognition, in which YCbCr has been used for segmentation and the Distance Transform method is adopted for feature extraction, 3 types of distance measures have been used such as City Block, Euclidean, and Chess Board, finally, Artificial Neural Network is used for the classification resulting in an accuracy of 91.11%.

An ISL recognition model is proposed by authors in [14] where the authors have used Sobel edge detector for segmentation and Direct pixel and Hierarchical centroid methods have been used for feature extraction and finally, Neural Network Pattern Recognition is used for classifying gestures into 10 classes resulting in an accuracy of 97.10%.

In [15] authors have used DWT based fusion of the Morphological subtraction model along with the Gradient-based Canny edge detection model for segmentation and Elliptical Fourier descriptors along with PCA has been used for Feature extraction. And finally, Artificial Neural Network is trained to perform the classification which gives an accuracy of 92.34% for classifying the input signs.

Leap Motion Controller has been used for segmentation and gesture capturing in [16] and the Euclidian Distance is used for feature extraction purposes. Going further Multilayer Perceptron Neural Network (MLP NN) model has been trained using the extracted features which then used for performing the classification of the hand gestures the model successfully recognized the numbers 0-9 with an accuracy of 100%.

Artificial Neural Network (ANN) based model has been suggested by authors in [17], in this paper segmentation is done by following the YCbCr mechanism and the features extractions are done using the HOG which consists of 4 levels such as Gradient Computation, Orientation Binning, Descriptor Blocks and Block Normalization, the ANN classification model has been trained using these features to predict the input gestures which result in 99% accuracy for identifying 10 numbers from 0-9.

Authors in [18] have used a selection of Effective Feature Techniques for segmentation followed by the Optimum Feature mechanism along with the Bayesian Classifier used for feature extraction which gives the accurate features needed for the classification and next Neural Network-based Particle Swarm Optimization(PSO) model known as NN PSO has been approached for gesture recognition with an accuracy of 99.96% for identifying the 22 gestures.

In [19] authors have used Discrete Cosine Transformation (DCT) along with PCA methods for Segmentation and the Feature Extraction is performed using the Euclidian, Normal Euclidian, and Mahalanobis distance metrics and finally, the Classification is done using the Artificial Neural Network which results in 90.58% accuracy for classifying 18 gestures.

Authors in [20] have used a Neural Network-based approach with a larger data set of 50,000, in this paper Joint distance topographic descriptor (JDTD) and Joint angle topographical descriptor (JATD) has been used for the Segmentation and Luminance based JDTD and JATD mechanism is applied for the Feature Extractions and finally, Convolutional Neural Network (CNN) model used to classify 500 variety of gestures with an accuracy of 92%.

A modified Long Short-term Memory-based architecture has been implemented in [21] where authors have used Leap motion-based sensor cameras for capturing the 3-D images, and the Segmentation is done with the help of the Leap Motion Sensor APIs. The Feature Extraction from the images is done using the 2D CNN which is forwarded to the LSTM model for prediction. The approached model gives an Accuracy of 72.30% for recognizing continuous sign language from 35 gestures.

Joint Angular Displacement Maps (JADMs) has been used by the authors in [22] for the segmentation process and Jet Color Map used to extract Spatio-Temporal Features from the 3-D images which are then fed to a CNN model whose architecture is designed following the Visual Geometry Group(VGG) architecture. This model gives an accuracy of 92.14% for recognizing 200 different gestures.

F. Conditional Random Fields (CRF)

Haar Classifier, Contour Matching has been used by authors in [23] for segmentation process and various features like geometric zones, features, templates, and global transformations, have been extracted from the images using different feature extraction techniques and then CRF based classifier is used for identifying the signs which give an accuracy of 86.00%.

G. Eigen Value Algorithm

Authors in [24] have applied the Shi-Tomasi method for segmentation and Harris Comer Detector has been used for feature extraction whereas for Categorization Minimum Eigen Value Algorithm is used and the features of the test images are compared with the features of the stored images in the database for identifying the gesture. The accuracy has not been disclosed by the authors.

H. Nearest Neighbor Classification

In [25] the authors have converted the RGB images to Gray Scale images then employed Otsu’s thresholding for segmentation and next the feature extraction is performed using the Fourier Descriptors and gets stored in the database following which the classification is done using the KNN and Cosine distance calculation method which gives an accuracy of 99.23%.

YCbCr has been used by authors in [26] for segmentation and the Fuzzy Membership Function is adopted for feature extraction after which the K-Nearest Neighbor Classification has been applied for recognition of the gestures which resulted in 84.82% accuracy.

Authors in [27] have applied multiple feature extraction and classification techniques and have predicted the accuracy of individual models and then proposed a model that combines several feature extraction and classification methodology for the better prediction of the gestures. In this paper, authors have used K-means clustering for Segmentation and Viewpoint Feature Histogram (VFH), SURF, Scale-invariant feature transform (SIFT) for feature extractions next the extracted features are stored using a k-tree index mechanism and finally the classification of the gestures done using a combination of SIFT Simple Weighted Majority (SIFT WM), SURF K-Nearest Neighbor Heuristic(SURF KNN), VFH K-Nearest Neighbor Heuristic (VFH KNN) and SURF prevails, on a majority of the voting concepts this model can predict 110 gestures with an accuracy of 90.68%.

I. Dynamic Time Warping (DTW)

Dynamic Time Warping technique has been used by authors in [28] where authors have performed the segmentation with the help of Skin color detection mechanism and Feature Vectors are prepared by extracting the required features from the images, next the DTW is used for prediction which predicts 24 classes of gestures resulting in a 90% accuracy.

J. Motionlet based adaptive kernel

Authors in [29] have introduced Motionlet based adaptive Joint Motion Segmentation Mechanism for the segmentation which is calculated using Gradient Distance and Mean Motion Threshold (MMT) methods, next Gross Joint Relative Distance (GJRD) Matrix is used for the feature extraction and finally, Adaptive Motionlet Kernels has been applied for the classification of the 500 different gestures which gives an accuracy of 98%.

A high-level summarization is given in “Table. 1” which will help the readers to know about various works and methodologies available in the literature.

IV. Proposed Methodologies

The proposed methodology for this research is presented in, Fig2.

The major steps of our proposed methodology are as follows.

A. Segmentation

After acquiring ISL datasets and performing the required pre-processing, segmentation will be performed. It is the process of segmenting the Region of Interest (ROI) from other parts of the input images, the extracted ROI is related to the gestures which can be used to train the model for differentiating the gestures from other contents of the image.

B. Feature Extraction using Metaheuristics

Feature Extraction is the most crucial step in SLR because the SL model processes the feature vectors retrieved from this step, therefore the feature extraction mechanism needs to be selected carefully so that the features can be extracted irrespective of orientation, position, and illumination.

In our research work, we are going to use Metaheuristic algorithms, these are a set of novel problem-solving methodologies and approaches that can be used for optimization.

C. ISLR Model Creation, Training & Testing

ISLR model will be a state of the art deep learning model, which will act as a brain of the application to classify the SLs and to produce the results. This model will undergo intensive training and fine-tuning process for predicting the ISLs with the highest accuracy.

ISLR Model Training is the learning phase of the ISLR model, in this phase, the model will get trained, on top of the previously created feature database. The main objective of the training process is to educate the model on how to map the input features with the output label [30].

ISLR Model Testing phase is going to evaluate the model training process by measuring the model's accuracy it also plays a vital role in the model tuning process.

To measure the proposed model’s performance, several metrics such as the correlation coefficient, Kappa statistic, Root Mean Square Error (RMSE), Mean Absolute Error(MAE), True Positive rate (TP rate), and F-measure will be calculated

D. Mobile App. Development and Embedding the ISLR Model

To make the model interact with the users seamlessly in

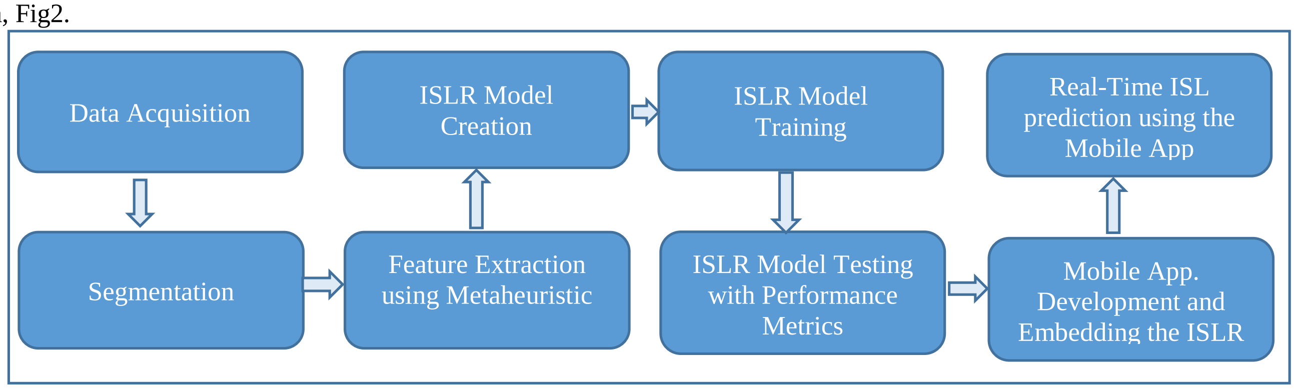

Fig. 2. Proposed Methodology

TABLE I. SUMMARIZATION OF AVAILABLE ISLR SYSTEMS

Methodology	Year	Segmentation	Feature Extraction	Classification	Classes	Data Set Size	Accuracy
SVM	[1]	YCbCr	PCBR, WPD-2	MSVM	26	986	91.30%
	[2]	Global Thresholding Algorithm	Structural Shape Descriptors	MSVM	60	720	96.00%
	[3]	HSV	Spatial Domain Method, Kalman Filter	MSVM	4	80	97.50%
	[4]	Edge Detection	Krawtchouk Moment, CFS	SVM PUK	26	1865	97.90%
	[5]	YCbCr	HOG	MSVM	11	500	NA
	[6]	K-Mean Clustering, Manhattan Distance	SURF, HOGLBP	SVM	140	4600	71.85%
Genetic Algorithm	[7]	HSV	Hausdorff Distance, Fourier Descriptor	Genetic Algorithm	26	NA	NA
Fuzzy Inference System	[8]	DWT, Canny Edge Detector	Fourier Descriptors	Sugeno type Fuzzy Inference System	80	1600	96.00%
Euclidean Distance	[9]	Microsoft Kinects 3Gear Technologies, B-Spline	Axis of List Inertia, Eigen Distance, PCA	Euclidean Distance	NA	NA	40.00%
	[10]	HSV, Histogram Matching	Eigen Value and Eigen Vector	Euclidean Distance	24	480	96.25%
	[11]	HSV, Median Filter	Orientation histogram, PCA	Euclidean Distance	10	50	93.00%
	[12]	Canny Edge Detection, YCbCr	Fourier Descriptors	Euclidean Distance	37	130000	97.50%
Neural Network	[13]	YCbCr	Distance Transformation	ANN	36	540	91.11%
	[14]	Sobel Edge Detector	Direct Pixel And Hierarchical Centroid	Neural Network	10	5000	97.10%
	[15]	Canny Edge Detection, DWT	Elliptical Fourier descriptors, PCA	ANN	80	720	92.34%
	[16]	Leap Motion Controller	Euclidian Distance	MLP	10	200	100%
	[17]	YCbCr	HOG	ANN	10	1000	99.00%
	[18]	Effective Features	Optimum Feature and Bayes Classifier	NN PSO	22	220	99.96%
	[19]	DCT, PCA	Euclidian and Mahalanobis Distance Metrics	ANN	18	180	90.58%
	[20]	JDTD, ATD	Luminance based JDTD and JATD	CNN	500	50000	92.00%
	[21]	LeapMotion Sensor	2D CNN	LSTM	35	942	72.30%
	[22]	JADMs	Spatio-Temporal Features	CNN based on VGG	200	20000	92.14%
Conditional Random Fields (CRF)	[23]	Haar Classifier, Contour Matching	Templates, Global Transformations	CRF	NA	NA	86.00%
Eigen Value algorithm	[24]	Shi-Tomasi Method	Harris Comer Detector	Min Eigen Value Algorithm	26	NA	NA
K-Nearest neighbor	[25]	Otsu's Thresholding	DWT	KNN, Cosine Distance	13	650	99.23%
	[26]	YCbCr	Fuzzy Membership Function	K-Nearest Neighbor Classification	26	1040	84.82%
	[27]	K-Means Clustering	VFH, SIFT and SURF, k-d tree	SIFT Weighted Majority, SURF KNN, VFH KNN with SURF	110	5041	90.68%
DTW	[28]	Skin Color Detection	Feature Vector	DTW	24	NA	90.00%
Motionlet based adaptive kernel	[29]	Joint Motion Segmentation , MMT	GJRD Matrix	Adaptive Motionlet Kernels	500	18000	98.00%

real-time and in the real world, we need to embed the ISLR model into a mobile app and this phase is responsible for developing a mobile-based application that is going to implant the ISLR model and acts as an interface between the real world and the ISLR model.

The application will receive an image or image-frames as input using the device cameras and sent them to the ISLR model for recognition, the ISLR processes it and gives the output, once the output is given by the model the application is going to convert the result into normal text or speech using the "Text to Speech" technologies and delivers it to the end-user.

E. Real-Time ISL prediction using the Mobile App.

The mobile application along with the ISLR model will be used to detect the real world ISLs, and in this phase, we are going to identify some of the potential users (Hearing challenged people) who are going to use it and based on the feedback given by the users, the application and the model will further fine-tuned.

V. CONCLUSION AND FUTURE WORKS

From literature search, it is observed that vision-based real-world dynamic ISLR is not yet explored by many researchers. With the recent advances in machine learning technology and related hardware support, development of ISLR is of paramount importance accordingly, so that more researchers will be involved in this research area. Further, more focus shall be given for developing the handheld devices or the apps for its deployment in the mobile devices. This way, it is envisaged that the proposed dynamic ISLR system shall be efficient for its real-world day-to-day applications in order to solve the communication problem of hearing-challenged people. Looking into the above discussions, development of a prototype is proposed as our future work.

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