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A Survey of Gesture Recognition Systems for Indian Sign Language Recognition

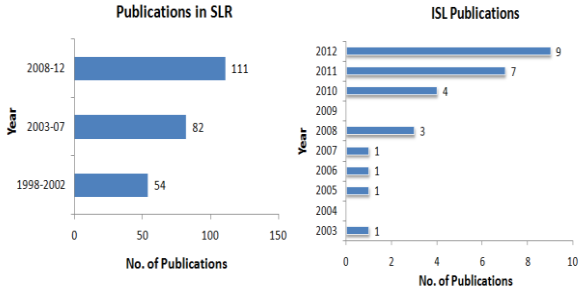
Komal Sheth, Nitish Gadgil, P. R. Futane

Abstract*— The problem of Sign Language Recognition (SLR) consists of four main stages, Video Acquisition, Video Processing, Feature Extraction and Recognition. SLR is a multi-disciplinary research area; hence literature survey of each stage mentioned above is done independently in order to find the suitable best method for each stage. Another reason for doing independent literature survey of each stage is, selection of efficient method at each stage will improve the overall performance of the SLR system. The set of techniques reviewed in this paper can be selected for developing a system for recognition of the native Indian Sign Language (ISL).

Keywords: SLR, ISL, Skin Detection, Feature Extraction.

I. INTRODUCTION

In the last few years there has been a great surge in the research related to the gesture recognition. Fig. 1(a) shows that the contribution in the field of SLR has increased considerably from the last decade. The sign language used in India is called as Indian Sign Language (ISL). ISL is not genetically related to any other Sign Language. The efforts to make a robust system for the recognition of ISL are increasing from the last decade as shown in the Fig. 1(b). ISL involves both static and dynamic gestures, single handed and double handed gestures, in addition to this the hands involved in gesturing may have complex motion. A thorough literature survey covering all the aspects of the SLR is a primary step to build a robust ISL recognition system.



(a) (b)

Fig. 1 Research trend in the field of SLR.

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II. VIDEO PROCESSING

Hand gesture recognition techniques rely heavily on the core image processing techniques for detection tracking and recognition [40]. The image segmentation separates the relevant data in the image from the background.

Use of the colored gloves limits the naturalness in performing and detecting the signs. To overcome this challenge a method to directly detect and segment skin color was developed [49]. The skin detection has gained a great attention due to the fact that skin color provides computationally effective yet, robust information against rotations, scaling and partial occlusions [27]. For detection of the body parts, the primary step is skin detection. Skin has a peculiar color created by the combination of blood (red) and melanin (yellow, brown) [50].

The factors that affect the use of skin color for the purpose of segmentation are explained in [27]. The contributions in the field of skin detection are summarized comprehensively in [9], [27], [31], and [46]. Efficiency of the skin detection approach depends on the two major aspects; skin color representation and skin segmentation, as shown in the fig. 2. Comparative assessment of the skin segmentation techniques can be found in [31]. Literature survey of these two aspects is done with the aim of selecting an optimum color space and segmentation method for the SLR system.

A. Skin Color Representation

The choice of the color space is the basis of the skin segmentation. All the color spaces can be obtained from linear or non-linear transformation of the basic RGB color space. Every color space provides unique advantages and has some limitations. The color space should reduce the overlap between skin and the non-skin pixels.

Table I provides the details about different color space used in the literature.

Table I. The Color Spaces used for the Skin Detection

Color Spaces	Work
RGB	[4], [20], [24], [25], [28],[35],[37],[41]
Normalized-RGB	[1], [6], [15], [35]
CIE-XYZ	[1], [6], [41]
HSI, HSV,HSL	[1], [4], [6], [11], [15], [28], [29], [35], [37], [41], [48]
TSL	[1], [15], [35], [47]
YCbCr	[1], [2], [3], [4], [6], [11], [14], [28], [36], [38], [41], [42]
CIE-Lab, CIE-Luv	[1], [6]. [21], [41]

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1) Basic Color Spaces

RGB corresponds to three colors: Red, Green and Blue. RGB color space has gained popularity among researchers for its simplicity of representation. But use of it for skin detection has some limitations; it cannot separate chrominance from luminance, it is highly susceptible to the illumination variation. In order to reduce its dependence on illumination, Normalized-RGB (rgb) is derived from RGB. The details about the advantages and limitations of rgb and the other color space, CIE-XYZ, are provided in [27].

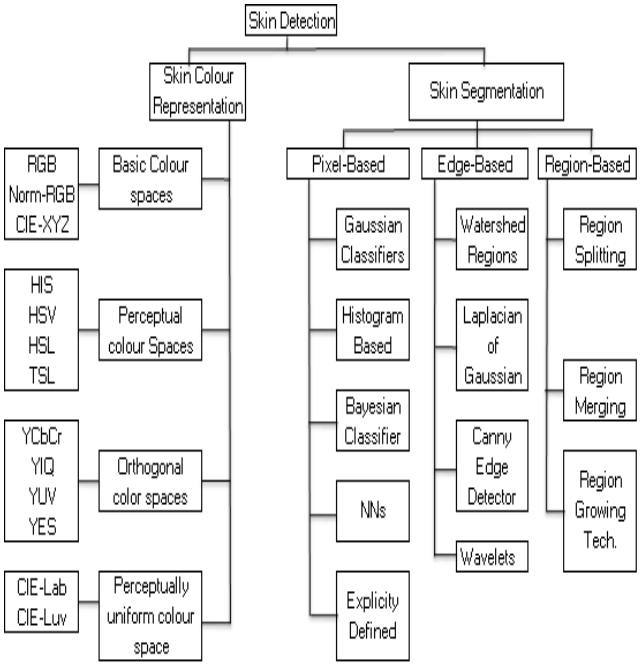

Fig. 2 Classification of the major aspects of skin detection

2) Perceptual Color Spaces

A Perfect definition of Hue, Saturation, Lightness and Tint is given in [27]. These color spaces are obtained by non-linear transformation of the RGB. The ability to discriminate between luminance and chrominance have made these color spaces very popular.

3) Orthogonal Color Spaces

These color spaces represents color with statistically independent components. YCbCr separates chrominance from luminance in the image as during the transformation from RGB, the Cb and Cr components are generated by subtracting the luminance (Y) component. Use of the YCbCr is popular among the researches because, the YCbCr has the same structure theory with person's vision [36]. Skin-color cluster is compact than that in RGB [2].

4) Perceptually Uniform Color Spaces

Perceptual uniformity represents how two colors differ in appearance to a human observer [27]. These are device independent color spaces. Luminance and chrominance are very well separated. Finally both are reasonably perceptually uniform color system [9]. But these color spaces are less popular because of its complex nature

B. Skin Color Representation

Survey of the most commonly used pixel-based skin segmentation method is given in this section. Table II gives the detailed analysis of the different pixel based skin segmentation approaches used in the literature. It is very difficult to choose the best segmentation method as all the approaches have evaluated their performance on different databases. The choice of segmentation method is affected by the application to be developed, the color space chosen for the skin representation. The detailed explanation of each technique is provided in [27], [46]. This section lists some of the advantages and limitations of the skin segmentation techniques

Table II. Summary of the Skin Segmentation Methods
I: Indoor; VI: Varying Illumination; CB: Complex Background.

Work	Input	Skin Detected	Color space	Method	Expt. Cond	Data-Base
[48]			Hsv	Explicit limits	I +VI+ CB	Own
[2]			YCbCr	Free form model	I+VI+ CB	Own
[20]			RGB	Ordinary Look Up Table	I + CB	Own
[41]			Five Color-s paces	Bayesian Look Up Table	I+O+ CB	ECU Face Data Base
[29]			HSV	Ordinary Look Up Table	I+O+ CB	Own
[34]			YCbCr	Gaussian Mixture Model (GMM)	I +O +VI+ CB	Own
[39]			YCbCr	GMM	CB	Own
[28]			RGB+ YCbCr + HSV	Explicit Limits	I +O	Own
[4]			RGB+ HSV+ YCbCr	Neural Network	I +VI	Own
[42]			YCbCr	Explicit Limits	I + VI	ORL

1) Explicitly Defined Skin Region (Explicit Limits)

This technique is popular due to its simplicity and lesser computational cost. However, the threshold values change with the color space. Accuracy is illumination dependent. It gives high true positive rate at the expense of high false positives [27]. The Skin colors of individuals cluster differently in the color space hence it is difficult to find the thresholds covering all the ethnic groups together without increasing the false positive rate.

2) Non-Parametric Modelling

These are fast both in training and classification. These are independent to the shape of skin distribution. The thresholds are set from the training images; hence these methods can be used to detect skin color of various ethnic groups with lesser false detection rate as compared with the explicitly defined skin region method. Unlike the parametric modelling methods their performance depends lesser on the choice of the color space.

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The performance of the non-parametric methods is better than that of the parametric methods [24]. However, these models lack the ability to interpolate the skin distribution, requires large training set for better accuracy. The performance of the model is affected by the degree of skin and non-skin overlap.

3) *Parametric Modelling*

A Comprehensive survey covering more than 100 publications of foreground and background modelling techniques using GMM is presented by [43].

These models can be trained with the lesser data compared to non-parametric models and have great ability to generalize the training data. However, these methods are computationally expensive because of the conventional Expectation-Maximization (EM) algorithm used for parameter estimation.

III. FEATURE EXTRACTION

After the skin segmentation, the features of an object of interest are extracted to express it in a compact form. Thus, it reduces the amount of resources required to describe a large set of data accurately.

Table III provides the summary of various feature extraction techniques used in the literature. There exist no correlation between the type of the classifier and the feature vector used for the gesture recognition. Type of gesture being recognized also plays crucial role in the selection of the feature extraction technique.

Physical features of the shape of the segmented hand contour can be used as feature vectors. This approach has been used in [48], the features related to moment of area, area and perimeter are used for the formation of a feature vector. This approach is simple and computationally fast but has a drawback that it depends on the size of the segmented hand and hence not user independent. The accuracy also reduces with the distance from the camera. So the features extracted are not scale invariant.

These features can give good result only with user dependent static gesture recognition system having less gesture vocabulary.

Principal Component Analysis (PCA) gives advantage of the reduced dimensionality [12]. This technique is used in the work of [12], [16]. However, PCA is very sensitive to the scaling, rotation and translation of the image and hence the image needs to be normalized before applying PCA [12]. PCA works better for the static gesture recognition than dynamic gesture recognition, as normalizing each frame before applying PCA becomes computationally inefficient.

Discrete Cosine Transform (DCT) is used in [10], [33]. The algorithm of the applying DCT to images is given in [8]. It has ability to pack the most information in the fewest coefficients as the human eye is most sensitive to the low frequencies. This technique is used mainly for static gesture recognition.

Orientation histograms are used in the work of [5], [19], [42]. The detailed algorithm for the implementation of orientation histograms is given in [19], [42]. It provides the local orientations of edges in sequence of images. It provides translation and illumination invariance. Orientation histograms can be used both for static and dynamic gesture recognition.

Table III. Summary of Various Feature Extraction Techniques used in the Literature

Work	Method	Gestures	Classifier
[3]	PCA and Linear Discriminant Analysis (LDA)	Static	RBFNN
[10]	coefficients of DCT	Static	Kohonen-Self Organizing Maps (SOM)
[12]	First 20 eigenvectors after performing PCA	Static	Bayes classifier
[42]	Orientation Histogram, PCA and Edge Ratio	Static	Support Vector Machine (SVM)
[5]	Orientation Histogram	Dynamic	Hidden Markov Model (HMM) and Bhattacharya Distance
[44]	Position and Shape of hand	Static and Dynamic	PCA, DHMM
[19]	Orientation Histogram	Static	Perceptron NN
[17]	Moment Features	Dynamic	HMM
[16]	PCA	Static	Weighted Euclidean Distance (Wt. Eu. Dist)
[14]	Principle Curvature Based Region (PCBR) detector, Wavelet Packet Decomposition (WPD-2)	Static and Dynamic	Multiclass Non-Linear SVM, DTW
[23]	Angular Radial Transform (ART)	Static and Dynamic	FSM
[22]	Static Features: Length of Trajectory, Number of Significant curve on Trajectory; Dynamic Features: Average Velocity, Standard Deviation of Velocity, Number of Minima of Velocity; ART	Dynamic	Dynamic Time Wrapping (DTW)

The state-of-the art survey of the feature detectors and features descriptors is given in [13]. The basic region based shape descriptors are discussed in this survey. Rests of the classes are out of the scope of this report. Angular Radial Transform (ART) as a feature descriptor is used in [23] for the purpose of indexing the FSMs on the basis of the first frame of the every gesture sequence. It was observed that the usage of ART gave fast retrieval performance during gesture recognition.

Angular Radial Partitioning (ARP) and ART feature descriptors have not been used extensively in the area of gesture recognition. Observing their individual invariance properties, their usage in the area of gesture recognition would be promising. These descriptors provide reduction in computational cost and reduction in memory required for storage. Table IV lists the invariant characteristics of the feature extraction techniques.

Table IV. Invariant Properties of Various Feature Extraction Techniques.

Feature	*Translation Invariance*	*Rotation Invariance*	*Scale Invariance*
Physical	Yes	No	No
PCA	No	No	No

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Orientation Histogram	Yes	No	Yes
ART	No	Yes	Yes
ARP	No	Yes	Yes

IV. GESTURE RECOGNITION

The final stage of any SLR system is gesture recognition. The input to the classifier can be presented by extracting the features from the input data using two altogether different approaches; Glove based Approach and Vision Based Approach for gesture recognition. Table V lists performance of some of the recognition techniques. The comprehensive surveys in the field of gesture recognition are given in [32], [40].

Data gloves were used in [26] for the purpose of giving input to the classifier. This method is not user friendly and hence is not very popular. Making use of gloves restricts the naturalness of the recognition system. However, the accuracy of recognition is more than the vision based approaches.

In order to overcome the limitations of the glove based system, a vision based recognition systems are developed, some of the vision based approaches are given in [3], [17], [22], and [42]. The vision based approach is user friendly, does not require a signer to wear the cumbersome gloves. However, using this approach to deal with the large vocabulary of gestures is a difficult task. The appearance of the gesture being recognized depends on the position of the camera, distance of the signer from the camera etc. These methods have to maintain a balance between accuracy and computational complexity during the real time performance. The major differences between these two approaches are given in [40].

A. *Neural Network*

The neural networks can be trained to perform complex tasks of recognition, classification etc. The two types of learning methodologies are explained in [3]. The basic network belonging to unsupervised learning class is Kohonen-Self Organizing Map (Kohonen-SOM). The basics of Kohonen network can be found in [30]. Kohonen-SOM was used in [10] for the classification of static gestures comprising some of the alphabets of ISL. The network could give accuracy of 80% for recognition of the static gestures.

Two commonly used networks of supervised learning class are Feed Forward Back Propagation Network (BPN) and Radial Basis Function Neural Network (RBFNN). RBFNN was used in [3] for the static gesture recognition of American Sign Language (ASL). Purdue RVL-SLLL ASL database was used for the experiments. The results with this network are very promising with 99% correct recognition accuracy. Feed forward BPN was used in [45] for the classification of static gestures involving alphabets of ASL with recognition accuracy of 92.78%.

Table V. Summary of Recognition Techniques used in the Literature

CI: Controlled Illumination; D: Dynamic; I: Indoor; S: Static; VI: Varying Illumination

Work	Gesture Type	Train/ Test	Data Base	Expt. Cond.	Method	%
[3]	S:6	300	ASL	I+ CI+VI	RBFNN	99
[12]	S:25	Train: 1000 Test:	ASL	I + CI	Bayes Method	99.7
		1500				
[44]	S: 28	Train: 3969 Test: 560	ISL and Own	I + CI	S: PCA	S: 94.5
	D: 17	Train: 340 Test: N/A			D: DHMM	D: 98
[17]	D: 60	Train: 600	Own	I + VI	HMM	82.7
[45]	S: 26	208	ASL	I + CI	BPNN	92.7
[16]	S: 24	Train: 240	ISL	I + CI	Wt. Eu. Dist.	97
[23]	S: 4	Train: N/A	Own	I + C I	FSM	S: 97 D: 84.8
	D: 10	Train: 500 Test: 250				
[22]	D: 10	1500	Own	I + CI	FSM	95.8
[10]	S:5	Train: 35 Test: N/A	ISL	I	Kohonen -SOM	80

Where, CI: Controlled Illumination; D: Dynamic; I: Indoor; S: Static; VI: Varying Illumination

The unsupervised learning methods are better at predicting the data than recognizing it [30]. RBFNN trains much faster than the Back propagation network. The advantages and limitations of using the neural network for the recognition purpose are given in [3], [19].

B. *Finite State Machine*

The theory, advantages and algorithm of FSM generation is briefed in [23].FSM was used in [23] for dynamic and static gesture recognition. The VOPs are extracted from the gesture sequence; subsequently KVOPs are extracted based on based on the Hausdorff distance measure along with their duration, thus creating a FSM. The accuracy obtained for local dynamic gestures is 84.8% and for static gestures it is 97%. FSM was used in [18] for the recognition of both static and dynamic gestures of ASL. The accuracy obtained for dynamic gesture was 61.33% and for static gestures 62.49%.

C. *Hidden Markov Model (HMM)*

In late 90s the HMM were the primary choice of the gesture recognition technique. A diagrammatic representation and explanation of the HMM is provided in [3]. HMM was used in [17] for the dynamic gesture recognition involving 60 different dynamic gestures. Recognition was performed using the Viterbi algorithm to estimate maximum likelihood state sequences. The recognition accuracy of 82.17% was achieved. HMM was also used in [18] for recognition of 26 dynamic gestures. The KVOPs are already extracted from the gesture sequence hence Viterbi algorithm was not used, as the algorithm is used to find only the probable sequence. Recognition accuracy of 69.83% was attained.

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V. CONCLUSION

- Choice of a color space and segmentation technique:

The color space chosen for skin representation should reduce the skin and non-skin pixel overlap. The orthogonal color spaces and perceptual color spaces show better chrominance and luminance separability and hence are the primary choice for the skin color representation. The performance of a color space is different for different segmentation methods. The "best pair" of color space and segmentation method should be selected based on the experimental results or the estimates provided in the literature. The choice depends on the trade- off between the accuracy and computational load.

- Choice Of The Feature:

The feature extraction reduces the computational time without sacrificing the accuracy. In order to design a flexible SLR system; the features of an image that are invariant to scaling, translation and rotation are necessary. Depending upon the characteristics of the feature extraction method, single or multiple features can be extracted to achieve such an overall invariance.

- Choice of Classifier:

There is a wide scope for selection of the classifier based on the speed and the complexity of the desired system. For the recognition of the dynamic gestures, HMM and FSM provides robust and faster alternative to the Neural Networks due to their simpler architecture.

The future work would be to select an efficient technique at each stage of the SLR. Based on those techniques, design and implement a SLR system which can recognize the static and dynamic gestures of the ISL

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