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Recent Developments in Indian Sign Language Recognition: An Analysis

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***Abstract* — There exists significant variation between sign language recognition processes across the world, although there are many similarities. Pre-processing, feature extraction and classification are the three major steps involved in the sign language recognition process. An analysis of scientific literature indicates the potential of various methods in achieving significantly high accuracy in image recognition. Further examination of the literature indicates the voluminous works carried out in American Sign Language recognition systems and most of these works compare the potential of various methods and combination of methods for their accuracy. Although, the comparison using randomly selected gestures for their potential would result in realistic overall accuracy for ASL where the gestures are simple and distinct, the complete adoption of such methods for Indian Sign Language (ISL) recognition may not be ideal due to the complexity in ISL. Other than static gestures, the dynamic gestures, gestures including facial expression, similarity in gestures, all increase the complexity of ISL. Therefore, the potential of different methods and their combinations need to evaluate in the context of ISL. A preliminary study to analyse the potential of promising feature extraction methods indicated that the methods could vary significantly while handling gestures with resemblances. This clearly indicates the necessity to screen gesture recognition methods for their accuracy in handling gestures in the context of complex ISL.**

***Keywords*— Indian Sign Language, Gesture Recognition, Preprocessing, Feature Extraction, Classification.**

I. INTRODUCTION

Sign languages have originated and evolved independently at different parts of the world. Sometimes, the connection with the native language and prevalent sign language are not very conspicuous. As an example, although British and Americans are predominantly native English speakers, their sign language differs significantly. American Sign Language(ASL) is single handed while handling alphabets, whereas British sign language (BSL) uses both hands except for the alphabet C(Perniss et al., 2007). There exists significant variation between sign languages across the world although there are similarities. The ASL, for instance has a strong connection with French sign language, similar is the case for Arabic sign language(Mohandes, 2013), however, the ASL varies significantly with BSL and Australian sign languages(Perniss et al., 2007).

There exist enormous complexity in Indian sign Languages and the challenges are manifold. Morgan M. W (1998) reviewed the Indian sign languages and inferred that the prevalent sign language has a strong South Indian Connection. Attempts have been made to have regional sign languages based on the local dialect and this further enhance the challenge of having a common and uniform ISL(Rajam and Balakrishnan, 2012). Other than static gestures, the dynamic gestures, gestures including facial expression, similarity in gestures all increases the complexity of ISL(Nandy et al., 2010). For example, slight variation in positioning of index finger on nose would interpret as "Think" or "Woman" in ISL(Morgan, 2009).Also, at interpretation level the language follows Subject-Object-Verb pattern contrary to ASL where S-V-O pattern is followed.

An analysis of scientific literature provide various methods in combination have yielded in significantly high accuracy in image recognition especially on an ASL context (Oz and Leu, 2011; Pugeault et al., 2011; Rashid et al., 2009; Wang et al., 2013). However, the total adoption of different methods is not possible for ISL. As explained, there exist postures in ISL with high resemblances, complex dynamic gestures, and facial expressions and similarity in gestures due to relative positioning of hand on hand and hand on face(Geetha and Manjusha, 2012; Ghotkar and Kharate, 2014; Nair and Bindu, 2013; Nandy et al., 2010). Therefore, various methods need to be screened for their accuracy in handling complex and difficult signs. This is very important as attempts are generally made using a set of randomly chosen gestures and the overall accuracy is predicted(Binh and Ejima, 2006; Cortes et al., 2006; Elons and Aboull-Ela, 2012; Kosmidou and Hadjileontiadis, 2010; Munib et al., 2007; Priyal and Bora, 2013; Rokade and Doye, 2011). However, the total postures and pattern are enormous in ISL and the potential of methods to handle complex selected signs would indicate the strength and weaknesses of each method and helps to arrive a combination of best methods. Therefore, this review tries to analyses the sign language computing globally and on an Indian context so that the potential of various methods to successfully interpret the Indian sign language are investigated.

II. COMPLEXITY OF INDIAN SIGN LANGUAGE

Indian sign language is quite complex in contrast to the ASL(Geetha and Manjusha, 2012; Johnson and Russell, 2008)where most of the gestures are performed with both the hands, complexity due to relative position of hand on hand and face, a higher proportion of dynamic gestures in expressing single postures(Geetha and Manjusha, 2012; Nair and Bindu, 2013; Nandy et al., 2010). In addition, one hand often moves faster than the other leading to complicated gesture postures(Geetha and Manjusha, 2012). Whereas the ASL is quite straight forward involving relatively simple hand gestures (Binh and Ejima, 2006; Rashid et al., 2009; Vogler et al., 1997). As discussed earlier, ASL uses single hand for most of the gestures(Perniss et al., 2007). Many works in global sign language computing use a set of static signs to test the accuracy level of different postures (Cortes et al., 2006; Elons and Aboull-Ela, 2012; Kosmidou and Hadjileontiadis, 2010; Munib et al., 2007; Priyal and Bora, 2013; Rokade and Doye, 2011). In ISL most of the gestures are dynamic involving both the hands as sequences of gestures(Geetha and Manjusha, 2012). In addition, at lexical level the complexity is enormous in ISL. There exist several types of hand gestures across the Indian continent. In a study, deaf and dumb schools in India were surveyed and found that significant variation in signs used(Johnson and Russell, 2008). In an attempt, the Ramakrishna Mission framed a Dictionary in collaboration with CBM International, Germany – to standardize ISL. In that attempt, the organization gathered signs from diversified sources (42 cities in 12 states) to provide a common sign language code for all over India (http://indiansignlanguage.org/history/),indicating the complexity of sign language data base. In addition, at interpretation level the ISL follows a Subject-Object-Verb (S-O-V) pattern in contrast to the S-V-O pattern in ASL. The thematic diagram (http://www.babysignlanguage.com/dictionary/a-d/) presented here explain this difference. Baby drinks milk in ASL will be sequenced as baby-milk-drinks in ISL (Figure 1).

III. AN ANALYSIS OF METHODS EMPLOYED IN SIGN LANGUAGE RECOGNITION

The sensor based recognition system uses cumbersome equipment such as gloves and kinetic sensor for the detection of images. These far from natural methods have a limited applicability due to the cumbersome equipment usage and user preference. Whereas the vision based gesture detection has the advantage of simplicity, user preference and relatively high accuracy. The detection involves primarily 3 steps such as pre-processing, feature extraction and classification (Fig 2) (Mitra and Acharya, 2007; Mohandes, 2013). The various methods employed in sign language recognition on a global scale are reviewed in this section to assess their suitability in recognising ISL purposes

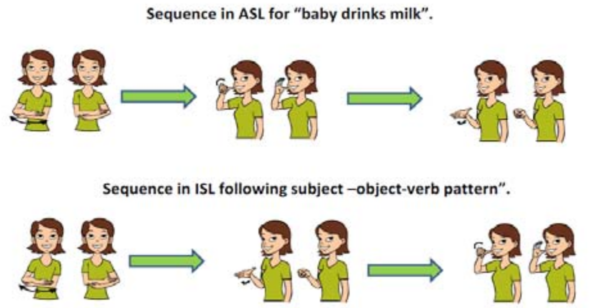

Fig:1 A comparison of ASL and ISL for their sentence sequence

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The segmentation is the primary and one of the major steps in data processing, in general, Otsu's algorithm provides a fairly high accuracy rate (Agrawal et al., 2012).Arabic sign language is more complex than ASL, deploying Hidden Markov model (HMM) and polynomial classifiers have yielded high recognition accuracy (96%) (Al-Rousan et al., 2009) and significant reduction in misclassifications(Assaleh and Al-Rousan, 2005), respectively. In another approach, the dynamic naive Bayesian classifiers (DNBCs) have shown high reliability in gesture recognition (Aviles-Arriaga et al., 2011) Haar method was utilised skin colour based segmentation and subsequently, a probabilistic model is developed for pose recognition of two-handed static hand pose recognition (ISL)(Bhuyan et al., 2011).In an attempt, the initialisation and segmentation steps are skipped by utilising a moving block distance parameterization approach. High accuracy rate (99 %) was achieved with reduced computational complexity, static signs and 33 basic word units are used in this study (Cortes et al., 2006). PCA in combination with local coordinate system yielded high computational accuracy and was found superior to a method based on condensation algorithm(Dan and Ohya, 2010).The use of Latent-Dynamic Conditional Random Fields (LDCRFs) in ASL yielded 96.14% recognition rate (Elmezain et al., 2012). . Employing HMMs resulted in 98.33% recognition rate when trained with Arabic numbers and ASL static gestures(Elmezain et al., 2009). PCA in combination with a multistage hierarchical classifier have given higher accuracy in recognition of Irish Sign Language shapes (Farouk et al., 2009).HMMs are successfully used to recognise signs for Australian sign language (Auslan). Tests using twenty signed words showed an accuracy level of 97% (Goh et al., 2006).The gesture description language (GDL) method is used to recognize static poses and body gestures and resulted in 80.5-98.5 %accuracy rate (Hachaj and Ogiela, 2014). The gesture recognition with a 3D Hopfield neural network (HNN) could achieve an accuracy rate of above 91 % (Huang and Huang, 1998).

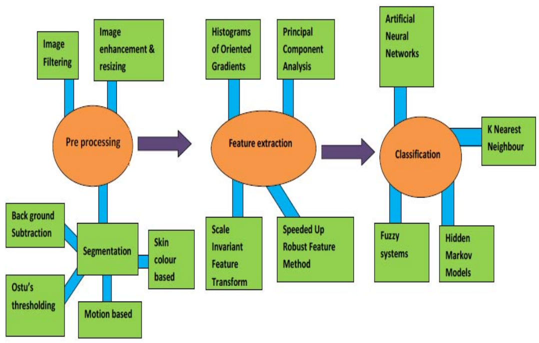

Fig:2 Major steps involved in sign language Recognition

Higher-order Local Auto-Correlation (HLAC) based features extraction based on HMM with skipping segmentation step and was found to be robust to variation illumination and background (Ishihara et al., 2004).An attempt has been made in converting Malaysian sign language into voice signals using Discrete Cosine Transform (DCT) in combination with neural network models gave an accuracy of 91%(Paulraj et al., 2008).The static images are converted with accuracy by using Binary-Decimal conversion algorithm for Tamil sign language, a subsidiary of ISL(Rajam and Balakrishnan, 2012).An approach based on dynamic Bayesian network (DBN),for ten isolated gestures yielded 99.59% accuracy (Suk et al., 2008).The local linear embedding procedure based recognition system resulted in an accuracy level of 90 % for Chinese sign language (CSL) alphabet (Teng et al., 2005). The segmental Boosted HMMs (SBHMMs), improves traditional HMM by reduction of error from 17% to 70% in American Sign Language recognition (Yin et al., 2008).

IV. Indian Sign Language Recognition

The Digital image processing techniques and artificial neural network were employed in recognising finger spelling in ISL (Adithya et al., 2013). In an approach, Otsu's algorithm was employed in segmentation and Scale Invariant Feature Transform and Histogram of Oriented Gradient were combined to evolve the feature vector. An accuracy level of 93% was achieved by this approach (Agrawal et al., 2012).The Artificial intelligence possibilities were utilised to convert the clerk's speech to signs played by a virtual 3D animated human character playing the signs corresponds to the speech in Malayalam (language of Kerala state, India) to ISL (Anuja et al., 2009).The number of finger tips and their distance from centroid is utilised together with PCA for Indian sign language recognition and high accuracy is achieved by this approach (Deora et al., 2012). In an attempt, Indian Sign Language (ISL) is recognised with 96% accuracy and translated to normal text. The Hu invariant moment and a multi-class Support Vector Machine (MSVM) is employed in the recognition process (Dixit and Jalal, 2013). An attempt has been made by extracting Maximum Curvature Points (MCPs) as key frames resulted in high accuracy for Indian Sign Language (ISL) (Geetha and Aswathi, 2013). The scalability problems of available recognition systems have minimised by segmentation based on Maximum Curvature Points (MCPs) and thus reduce the requirement of large training data set and reduce the complexity (Geetha et al., 2013). In an attempt, classification is performed using direction histogram due to high performance for illumination and invariance of orientation. The approaches based on K-nearest neighbour metrics and Euclidean distance resulted in high performance in recognising ISL (Nandy et al., 2010). The Table 1 indicates the most dominating research works done on ISL.

V. Conclusions

The overall analysis of selected review (based on Web of Science citations') clearly indicates the advancement of sign language recognition research globally and on an Indian context. Apart from few promising works, most of the research works use static gestures for validation. As discussed earlier, the complexity of ISL is high and the ISL evolved irrespective of computational convenience and based on huge lexical complexity. Therefore, research works should address the potential of different approaches to tackle the complexity of ISL.

TABLE I
Research works done on ISL

Ref. No	**Author & Year**	**Description**	**Gestures set**
[35]	Nandy et al 2009	Orientation histogram was used to extract feature and classification was done using KNN and Euclidean distance.	Set of words
[1]	Rekha et al 2010	Principle Curvature Based region with wavelet packet decomposition extraction and classification was done using Multiclass SVM.	Static gesture and Dynamic gestures Representi ng words
[4]	Adithya et al 2013	Segmentation using Otsu's algorithm. SIFT & HOG for feature extraction and classification using ANN	Finger spelling
[14]	Deora et al 2012	Number of figure tips and there distance from centroid together with PCA was used as feature descriptor	Alphabets and numbers
[22]	Geetha et al 2013	Maximum Curvature Point as key frames or gesture shape identification.	Alphabet
[2]	Neha et al 2014	HOG feature extractor with NN classifier	Double hand 18 ISL alphabet
[3]	Shweta et al 2013	Centre of gestures ,distance of measure to boundary and degree measure as feature measure and ANFIS as classifier	Alphabets

REFERENCES

[1] Rekha J., J. Bhattacharya and S. Majumder. 2011. Shape, texture and local movement hand gesture features for Indian Sign Language recognition. 3rd International Conference on Trends in Information Sciences and Computing (TISC). : 30-35.

[2] Neha V. Tavari, Prof. A. V. Deorankar,'Indian Sign Language Recognition based on Histograms of Oriented Gradient' , International
Journal of Computer Science and Information Technologies, Vol. 5 (3) 2014, 3657-3660

[3] Shweta Dour and J M Kundargi. Article: Design of ANFIS System for Recognition of Single Hand and Two Hand Signs for Indian Sign Language. *IJAIS Proceedings on International Conference and workshop on Advanced Computing 2013* ICWAC(2):18-25, June 2013. Published by Foundation of Computer Science, New York, USA.

[4] Adithya, V., Vinod, P. R., Gopalakrishnan, U., and Ieee (2013). "Artificial Neural Network Based Method for Indian Sign Language Recognition."

[5] Agrawal, S. C., Jalal, A. S., Bhatnagar, C., and Ieee (2012). "Recognition of Indian Sign Language using Feature Fusion."

[6] Al-Rousan, M., Assaleh, K., and Tala'a, A. (2009). Video-based signer-independent Arabic sign language recognition using hidden Markov models. *Applied Soft Computing* **9**, 990-999.

[7] Anuja, K., Suryapriya, S., and Idicula, S. M. (2009). Design and Development of a Frame Based MT System for English-to-ISL. *In* "2009 World Congress on Nature & Biologically Inspired Computing" (A. Abraham, F. Herrera, A. Carvalho and V. Pai, eds.), pp. 1381-1386.

[8] Assaleh, K., and Al-Rousan, M. (2005). Recognition of Arabic sign language alphabet using polynomial classifiers. *Eurasip Journal on Applied Signal Processing* **2005**, 2136-2145.

[9] Aviles-Arriaga, H. H., Sucar-Succar, L. E., Mendoza-Duran, C. E., and Pineda-Cortes, L. A. (2011). A Comparison of Dynamic Naive Bayesian Classifiers and Hidden Markov Models for Gesture Recognition. *Journal of Applied Research and Technology* **9**, 81-102.

[10] Bhuyan, M. K., Kar, M. K., and Neog, D. R. (2011). Finger Tips Detection for Two Handed Gesture Recognition. *International Conference on Graphic and Image Processing (Icgip 2011)* **8285**.

[11] Binh, N. D., and Ejima, T. (2006). "A new approach dedicated to hand gesture recognition."

[12] Cortes, G., Garcia, L., Benitez, C., Segura, J. C., and Isca (2006). "HMM-Based Continuous Sign Language Recognition using a Fast Optical Flow Parameterization of Visual Information."

[13] Dan, L., and Ohya, J. (2010). Study of Recognizing Multiple Persons' Complicated Hand Gestures from the Video Sequence Acquired by a Moving Camera. *In* "Human Vision and Electronic Imaging Xv" (B. E. Rogowitz and T. N. Pappas, eds.), Vol. 7527.

[14] Deora, D., Bajaj, N., and Ieee (2012). "INDIAN SIGN LANGUAGE RECOGNITION."

[15] Dixit, K., and Jalal, A. S. (2013). Automatic Indian Sign Language Recognition System. *Proceedings of the 2013 3rd Ieee International Advance Computing Conference (Iacc)*, 883-887.

[16] Elmezain, M., Al-Hamadi, A., and Ieee (2012). LDCRFs-Based Hand Gesture Recognition. *In* "Proceedings 2012 Ieee International Conference on Systems, Man, and Cybernetics", pp. 2670-2675.

[17] Elmezain, M., Al-Hamadi, A., Pathan, S. S., and Michaelis, B. (2009). "Spatio-Temporal Feature Extraction-Based Hand Gesture Recognition for Isolated American Sign Language and Arabic Numbers."

[18] Elons, A. S., and Aboull-Ela, M. (2012). Arabic Sign Language Recognition System Based on Adaptive Pulse-Coupled Neural Network. *In* "Advanced Machine Learning Technologies and Applications" (A. E. Hassanien, A. B. M. Salem, R. Ramadan and T. H. Kim, eds.), Vol. 322, pp. 213-221.

[19] Farouk, M., Sutherland, A., and Shoukry, A. A. (2009). "A Multistage Hierarchical Algorithm for Hand Shape Recognition."

[20] Geetha, M., and Aswathi, P. V. (2013). Dynamic Gesture recognition of Indian Sign Language considering Local motion of hand using Spatial location of Key Maximum Curvature Points. *2013 Ieee Recent Advances in Intelligent Computational Systems (Raics)*, 86-91.

[21] Geetha, M., Aswathi, P. V., Kaimal, M. R., and Ieee (2013). A Stroke based representation of Indian Sign Language Signs incorporating Global and Local motion information. *2013 Second International Conference on Advanced Computing, Networking and Security (Adcons 2013)*, 62-67.

[22] Geetha, M., and Manjusha, U. C. (2012). A Vision Based Recognition of Indian Sign Language Alphabets and Numerals Using B-Spline Approximation. *International Journal on Computer Science and Engineering* **4**, 406-415.

[23] Ghotkar, A. S., and Kharate, G. K. (2014). STUDY OF VISION BASED HAND GESTURE RECOGNITION USING INDIAN SIGN LANGUAGE. *INTERNATIONAL JOURNAL ON SMART SENSING AND INTELLIGENT SYSTEMS* **7**, 96-114.

[24] Goh, P., Holden, E.-J., and Ieee (2006). Dynamic fingerspelling recognition using geometric and motion features. *In* "2006 IEEE International Conference on Image Processing, ICIP 2006, Proceedings", pp. 2741-2744.

[25] Hachaj, T., and Ogiela, M. R. (2014). Rule-based approach to recognizing human body poses and gestures in real time. *Multimedia Systems* **20**, 81-99.

[26] Huang, C. L., and Huang, W. Y. (1998). Sign language recognition using model-based tracking and a 3D Hopfield neural network. *Machine Vision and Applications* **10**, 292-307.

[27] Ishihara, T., Otsu, N., and ieee computer, s. (2004). "Gesture recognition using auto-regressive coefficients of higher-order local auto-correlation features."

[28] Johnson, J. E., and Russell, J. J. (2008). Assessment of Regional Language Varieties in Indian Sign Language. *SIL Electronic Survey Report 2008-006*, 1-121.

[29] Kosmidou, V. E., and Hadjileontiadis, L. I. (2010). Using sample entropy for automated sign language recognition on sEMG and accelerometer data. *Medical & Biological Engineering & Computing* **48**, 255-267.

[30] Mitra, S., and Acharya, T. (2007). Gesture recognition: A survey. Ieee Transactions on Systems Man and Cybernetics Part C-Applications and Reviews **37**, 311-324.

[31] Mohandes, M. A. (2013). Recognition of Two-Handed Arabic Signs Using the CyberGlove. *Arabian Journal for Science and Engineering* **38**, 669-677.

[32] Morgan, M. W. (2009). Typology of Indian Sign Language Verbs from a Comparative Perspective. *In* "Annual Review of South Asian Languages and Linguistics 2009" (R. Singh, ed.), Vol. 222, pp. 103-131.

[33] Munib, Q., Habeeb, M., Takruri, B., and Al-Malik, H. A. (2007). American sign language (ASL) recognition based on Hough transform and neural networks. *Expert Systems with Applications* **32**, 24-37.

[34] Nair, V. A., and Bindu, V. (2013). A Review on Indian Sign Language Recognition. *International Journal of Computer Applications* **73**.

[35] Nandy, A., Prasad, J. S., Mondal, S., Chakraborty, P., and Nandi, G. C. (2010). Recognition of Isolated Indian Sign Language Gesture in Real Time. *In* "Information Processing and Management" (V. V. Das, R. Vijayakumar, N. C. Debnath, J. Stephen, N. Meghanathan, S. Sankaranarayanan, P. M. Thankachan, F. L. Gaol and N. Thankachan, eds.), Vol. 70, pp. 102-107.

[36] Oz, C., and Leu, M. C. (2011). American Sign Language word recognition with a sensory glove using artificial neural networks. *Engineering Applications of Artificial Intelligence* **24**, 1204-1213.

[37] Paulraj, M. P., Yaacob, S., Desa, H., Hema, C. R., Ab Majid, W. M. R. W., and Ieee (2008). "Extraction of Head and Hand Gesture Features for Recognition of Sign Language."

[38] Perniss, P. M., Pfau, R., and Steinbach, M. (2007). Visible variation: Comparative studies on Sign Language Structure. *Mounton De Gruyter, Berlin, Germany*, 1-411.

[39] Priyal, S. P., and Bora, P. K. (2013). A robust static hand gesture recognition system using geometry based normalizations and Krawtchouk moments. *Pattern Recognition* **46**, 2202-2219.

[40] Pugeault, N., Bowden, R., and Ieee (2011). Spelling It Out: Real-Time ASL Fingerspelling Recognition. *2011 Ieee International Conference on Computer Vision Workshops (Iccv Workshops)*.

[41] Rajam, P. S., and Balakrishnan, G. (2012). Recognition of Tamil Sign Language Alphabet using Image Processing to aid Deaf-Dumb People. *In* "International Conference on Communication Technology and System Design 2011" (E. P. Sumesh, ed.), Vol. 30, pp. 861-868.

[42] Rashid, O., Al-Hamadi, A., and Michaelis, B. (2009). "A Framework for the Integration of Gesture and Posture Recognition Using HMM and SVM."

[43] Rokade, R. S., and Doye, D. (2011). Static Hand Gesture Recognition from a Video. *International Conference on Graphic and Image Processing (Icgip 2011)***8285**.

[44] Suk, H.-I., Sin, B.-K., Lee, S.-W., and Ieee (2008). "Recognizing Hand Gestures using Dynamic Bayesian Network."

[45] Teng, X. L., Wu, B., Yu, W. W., and Liu, C. Q. (2005). A hand gesture recognition system based on local linear embedding. *Journal of Visual Languages and Computing***16**, 442-454.

[46] Vogler, C., Metaxas, D., and Ieee (1997). Adapting hidden Markov models for ASL recognition by using three-dimensional computer vision methods. *In* "Smc '97 Conference Proceedings - 1997 Ieee International Conference on Systems, Man, and Cybernetics, Vols 1-5: Conference Theme: Computational Cybernetics and Simulation", pp. 156-161.

[47] Wang, Y., Yang, R., and Ieee (2013). REAL-TIME HAND POSTURE RECOGNITION BASED ON HAND DOMINANT LINE USING KINECT. *Electronic Proceedings of the 2013 Ieee International Conference on Multimedia and Expo Workshops (Icmew)*.

[48] Yin, P., Essa, I., Starner, T., Rehg, J. M., and Ieee (2008). Discriminative feature selection for hidden Markov models using segmental boosting. *In* "2008 Ieee International Conference on Acoustics, Speech and Signal Processing, Vols 1-12", pp. 2001-2004.