

A Real-Time Appearance-Based Bengali Alphabet And Numeral Signs Recognition System

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ABSTRACT

This paper presents a real-time appearance-based Bengali alphabet and numeral signs recognition system. Region of Interest (ROI) is initialized by detecting 'Opened Hand' followed by 'Closed Hand' posture from captured images using Haar cascade classifiers. Probable hand area is segmented based on Hue and Saturation values of human skin color from ROI. Segmented image has been converted to binary image and resized it to predefine resolution (150×150). Row vectors are generated from the binary images to train and/or test the system. Hand postures are classified using K-Nearest Neighbors (KNN) classifier. The system is trained using 3600 (36×10×10) images of 36 Bengali alphabets and 1000 (10×10×10) images of 10 numeral signs, from 10 performers. The system is tested using 7200 images of alphabets and 2000 images of numeral signs. Among which, 3600 images of alphabets and 1000 images of numerals were collected from who didn't participate in training process. Experimental results show satisfactory classification accuracies in real-time.

Keywords: Hand posture, Skin color based segmentation, KNN Classifier, Bengali Sign Language (BdSL).

1. Introduction

Sign language is a separate language with its own grammar and rules that is highly structured and has well defined meanings. Speech or hearing impaired people use sign language to communicate with other people and among themselves. Bengali Sign Language (BdSL) is originated based on modified form of British, American and Australian sign languages and some local indigenous signs [1]. BdSL is structurally different from sign languages of other countries. To represent BdSL alphabets, both hands are used generally but single hand is used to represent Bengali numeral signs. In 1994, Bangladesh Sign Language Committee [2], introduced a Bengali sign language dictionary which uses 36 (6 vowels and 30 consonants) two-handed Bengali sign alphabets from 51 Bengali written alphabets according to pronunciation. The system uses these 6 vowels (অ, আ, ই, উ, এ, ও) and 30 consonants (ক, খ, গ, ঘ, চ, ছ, জ, ঝ, ট, ঠ, ড, ঢ, ত, থ, দ, ধ, ন, প, ফ, ব, ভ, ম, য়, র, ল, স, হ, ঙ, ঞ) of BdSL alphabet signs and 10 BdSL numeral signs (০, ১, ২, ৩, ৪, ৫, ৬, ৭, ৮, ৯) for training and testing process.

Many researchers have attempted to develop sign language recognition system in different countries. Kulkarni et al. [3] developed an American Sign Language (ASL) recognition system using appearance based method. British Sign Language (BSL) recognition system was developed using multi-class classifier based on Sequential Pattern Trees by Ong et al. [4]. Naoum et al [5] developed an Arabic sign language (ArSL) recognition system using KNN classifier. Japanese Sign Language (JSL) recognition system was developed using Hidden Markov Model (HMM) by Sako et

al. [6] and Australian Sign Language (AuSL) recognition system was developed using HMM by Eun-Jung Holden et al. [7]. In Bangladesh, Eshaque et al. [8] developed an intelligent assistant system, which could understand ten Bengali expressions using only single hand. D. S. H. Pavel et al. [9] developed a model of Bengali sign language expressions by using geometric model of hand. The system displays only single handed gesture for only 20 signs with 97% accuracy. Another system was developed by D. S. H. Pavel et al. [10] which analyzes video clips of different gestures of BdSL taken as input and gives a regular language expression as an audio output. S. Begum et al.[1] developed a computer vision-based BdSL recognition system which recognize static 6 Bengali Vowels and 10 Bengali Number signs using Principal Component Analysis (PCA) with average Precision rate of 82% and average Recall rate of 80%. F. M. Rahim et al. [11] developed an intelligent sign language verification system using image processing, clustering and Neural Network (NN) Concepts with satisfied results. K. Deb et al. [12] presented a new BdSL recognition method using template matching technique with the use of normalized cross-correlation to perform two different color wrist band regions and filtering. M. A. Rahman et al. [13] presented a simple model of BdSL alphabet recognition system using Artificial Neural Network (ANN) which was able to recognize 36 BdSL alphabets performed by both hands with an average accuracy of 80.902%. B. C. Karmokar et al. [14] developed a BdSL recognition system involving different numbers of individual Neural Networks (NNs) in negative correlation learning (NCL) with accuracy of 93%. M. Jasim et al. [15] developed a real-time system for recognizing static and dynamic hand gesture using KNN algorithm and Longest Common Subsequence (LCS) analysis algorithm respectively with good accuracy.

The limitations of existing sign language recognition systems include low recognition rate in cluttered background and illumination varying environment, environmental noise, training scenarios and high computational cost. To address these issues, we propose a Bengali sign language recognition system that is performer independent and can recognize in real-time. The proposed system uses Haar cascade classifiers and skin-color segmentation method in combination to detect the probable hand area in illumination and background variation environment. To reduce the environmental noise, our proposed system applies morphological operations (dilation and erosion) and Gaussian smoothing filter sequentially on the segmented hand area. The proposed system minimizes the computational costs by using only row vectors from hand image as features instead of using multiple features. Use of large training image database from 10 different performers (where 6 are males and 4 are female) makes the system performer independent. The previous system [16] recognized only 36 BdSL Alphabet signs in controlled environment. The proposed system recognizes 36 Alphabet signs performed by both hands and 10 Bengali numeral signs performed by single hand in illumination and background variation environment. The proposed system (BdSLR) performs better in compare with the existing reputed BdSL recognition systems developed by S. Begum et al.[1]; M. Jasim et al. [15]; and M. A. Rahman et al. [13] for the same dataset and environment. The system is applicable for human machine communication using BdSL alphabets and numeral signs. It may be used as a tool to communicate with sign and non-sign people. The rest of the paper is organized as follows. Section 2 describes the proposed system. Section 3 presents the experimental result with discussion. Finally, the paper is concluded in Section 4.

2. Proposed System Description

Fig.1 presents the block diagram of the proposed Bengali alphabet and numeral sign recognition system. The proposed system uses a USB or CCD camera to capture image with a resolution of 640×480. The system is briefly described in following sub-sections.

2.1 Hand Area Detection and ROI Initialization

The system detects the ‘Opened Hand’ posture followed by a ‘Closed Hand’ posture using Haar cascade classifiers [17] from the captured image and initializes the ROI based on detected area [16]. User can reset the ROI by repeating those postures.

2.2 Preprocessing and Segmentation

In the preprocessing module, the system crops the ROI and segments human skin color by applying threshold values on Hue (H) and Saturation (S) in HSV color coordinate system [16]. This values are measured from people of different skin color from various racial majority [18], and also under different lighting conditions as well. Example output of skin color based hand posture segmentation is shown in Fig. 2(b).

After segmentation, the system applies noise removal techniques such as morphological filtering (dilation and erosion) and smoothing filter to reduce noise [19] using Eq.(1), Eq.(2) and Eq.(3) respectively.

$$A' = A \oplus B = \{z | (B'_z) \cap A \neq \phi\} \quad (1)$$

Where, A is segmented image which is dilated by the structuring element B in set of all points Z and the dilated image is represented by A'. In the Fig. 2(b), red marked boxes indicate the small gaps that arise due to skin color based segmentation. These are removed by the dilation operation using Eq.(1) and the example output of dilation operation is shown in Fig. 2(c). Then the system erodes the dilated image A' by the structuring element B in Z and the resulted image A'' from erosion is prepared by using Eq.(2).

$$A'' = A' \ominus B = \{z | (B_z) \subseteq A'\} \quad (2)$$

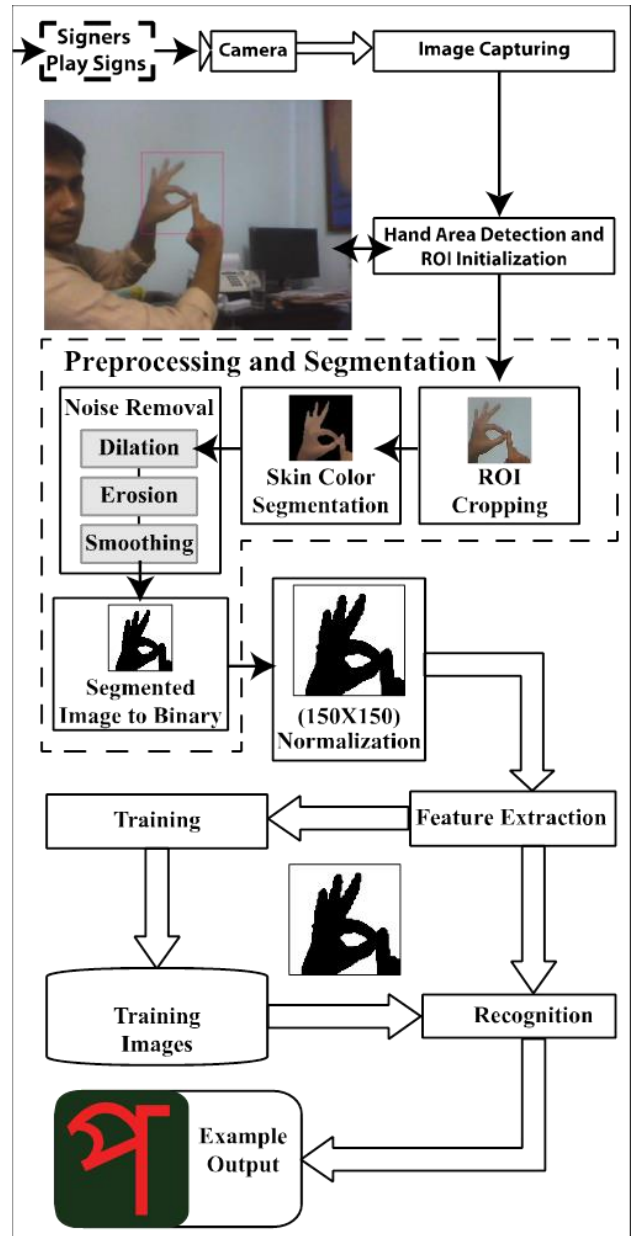


Fig. 1: Block diagram of the proposed system.

In the Fig. 2(b) and Fig. 2(c), red marked circle indicates the unwanted dots or noise which arise due to skin color based segmentation and is removed by the erosion operation using Eq.(2) and the example output of the erosion operation is shown in Fig. 2(d). After completion of morphological operation dilation and erosion, the system uses Gaussian smoothing with a filter of 5×5 kernel by using the Eq.(3).

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

Where, x and y are the horizontal and vertical distance from the origin of the eroded image A'' and σ is the standard deviation of the Gaussian distribution. Fig. 2(e) shows the example output of the smoothed image of hand posture. After removing the noise, the segmented image is converted to binary image using Eq.(4).

$$f(x, y) = \begin{cases} 1 & \text{if } V(P) \in \text{Skin}(x, y) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where, $V(P)$ represents the pixel value of segmented image; $\text{Skin}(x, y)$ represents the skin color region of the segmented image and $f(x, y)$ is the resulted binary image containing pixel value 0 and 1. The final output of the preprocessing module of the system is the binary image as shown in Fig. 2(f).

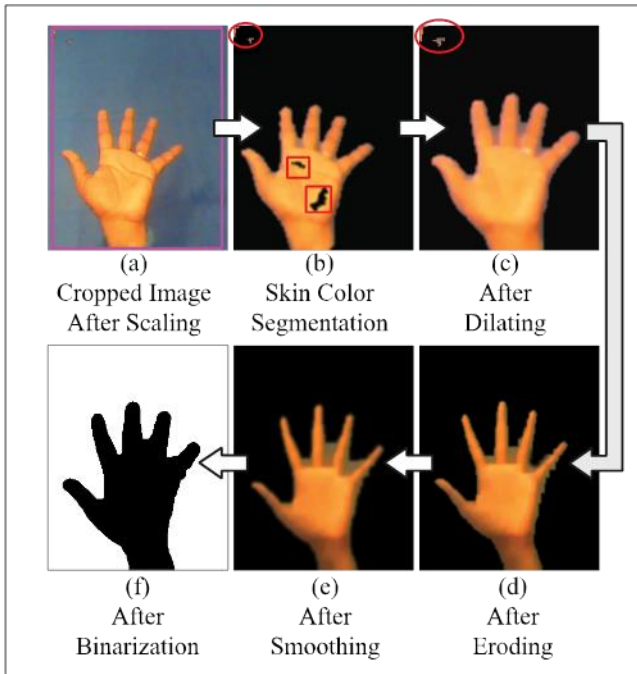


Fig. 2: Example results after preprocessing.

2.3 Normalization and Feature Extraction

After preprocessing and segmentation, the system normalizes the variable sizes of binary images into a specific size (150×150). The system extracts row vector, $T_i^j = [r_0c_0, r_0c_1, r_0c_2, \dots, r_0c_{149}, r_1c_0, r_1c_1, r_1c_2, \dots, r_1c_{149}, r_2c_0, r_2c_1, r_2c_2, \dots, r_2c_{149}, \dots, r_{149}c_0, r_{149}c_1, r_{149}c_2, \dots, r_{149}c_{149}]$

as a feature vector from each normalized binary image where, $r_p c_q$ represents the pixel value ('0' or '1') corresponding P^{th} row and Q^{th} column of the normalized binary image. Our proposed system uses only row vector as a feature vector instead of multiple features for training and recognition which reduces the computational cost.

2.4 Training Process

In the training phase, the KNN classifier [20] is only performed for storing feature vectors of normalized binary images and class labels of training data sets. For each sign X_i , the system generates 100 feature vectors ($[T_i^0], [T_i^1], [T_i^2], \dots, [T_i^{99}]$). Finally, the system stores each feature vectors, T_i^j into the corresponding sign class, i for each sign X_i . Separate KNN classifiers are trained for Bengali alphabet and numeral signs with different K values. For the system training, we measured the Accuracy versus computational costs to fine-tune the values of K for Bengali alphabet and numeral signs using the selected off-line samples of hand postures. From the observations, we decide that the value of K is 7 for alphabet signs and the value of K is 5 for numeral signs are set for achieving the high Accuracy with reduced computational costs.

The input hand postures of 36 Bengali alphabet signs (অ, আ, ই, উ, এ, ও, ক, খ, গ, ঘ, চ, ছ, জ, ঝ, ঞ, ট, ঠ, ড, ঢ, ত, থ, দ, ধ, ণ, প, ফ, ব, ভ, ম, য়, র, ল, স, হ, ঙ, ঞ, ঔ) are to be assigned to the alphabet class labels of $\{0, 1, 2, \dots, 35\}$ respectively and the input hand postures of 10 Bengali numeral signs (০, ১, ২, ৩, ৪, ৫, ৬, ৭, ৮, ৯) are to be assigned to the numeral class labels of $\{0, 1, 2, \dots, 9\}$ respectively in separate training image databases. The example of training dataset of BdSL Alphabets are presented in Fig. 3 and BdSL numerals are presented in Fig. 4.

2.5 Recognition Process

In the recognition module, the extracted normalized binary hand postures are classified or recognized by comparing with pre-trained binary images of hand postures using KNN Classifier. When the extracted feature vector Γ of the test image is matched with the pre-stored trained feature vectors T_i^j of the hand posture, the system returns a class label containing the specific hand posture of BdSL alphabet or numeral signs with the maximum of 'K' instances which will be the recognized sign class for the feature vector, Γ of the test image. The system applies KNN algorithm to find the K nearest trained feature vector T_i^j to feature vector Γ of test image based on minimum Euclidian distance, $Min|\delta(\Gamma, T_i^j)|$ with $\delta(\Gamma, T_i^j) \geq 0$ which is measured by using Eq.(5).

$$\delta(\Gamma, T_i^j) = \sqrt{\sum(\Gamma - T_i^j)^2} \quad (5)$$

3. Experimental Result and Discussion

The proposed system uses an ASUS A42F series laptop with Intel Corei3 processor of 2.40 GHz and 2GB RAM.

The system uses a built-in webcam of ASUS A42F series laptop for image acquisition. Microsoft visual studio 2008 and EmguCV (C# and OpenCV wrapper) [21] are used in 32-bit operating system of MS Windwos7, as system development platform.

3.1 Training Images Database

Fig.3 presents the example set of Bengali alphabets (6 vowels and 30 consonants) training dataset and Fig.4 presents the example set of Bengali numeral signs training dataset.



Fig. 3: Example postures of (a) Vowel signs and (b) Consonant signs of BdSL Alphabet signs.

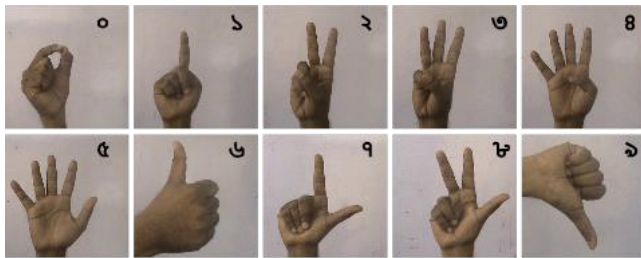


Fig. 4: Example postures of BdSL Numeral signs.

The proposed system is trained separately for 36 hand postures of BdSL alphabets and 10 hand postures of BdSL numerals. 10 images of each predefined hand postures are captured from each performer for training the system. 10 different performers perform those signs, where four are female and six are male. This resulted in 3600 (10×10×36) training images for Bengali alphabet signs and 1000(10×10×10) training images for Bengali numeral signs (০ to ৯).

3.2 Recognition Performance Analysis

For testing the system, two cases are considered.

Case-1(C1): Test data and training data are prepared in same environment from same 10 performers, where 10×10=100 samples for each sign are prepared for training and another 10×10=100 samples for each sign are prepared for testing.

Case-2(C2): Test data are prepared in different environments from 10 new performers who are not included in training phase, where 10×10=100 samples for each sign are prepared for testing.

The system uses five performance parameters such as: Precision, Recall, F-measure, Accuracy and Computational Cost. Those are calculated using Eq.(6), Eq.(7), Eq.(8), Eq.(9) [22] and Eq.(10) respectively.

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F - measure (F1) = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

$$Computational Cost = T1 + T2 + T3 + T4 \quad (10)$$

The values of TP, TN, FP and FN are generated from separate confusion matrixes for both cases (C1 and C2) of BdSL alphabets and numerals recognition which are not shown in here for simplicity. T1,T2,T3 and T4 represents the time to capture an image, preprocess, extract features and match it with the training dataset in milliseconds per frame.

Table 1 presents the summarized results of 36 BdSL alphabets recognition considering both cases (C1 and C2). From the test results shown in Table 1, it is evident that BdSL alphabets are recognized and distinguished with the average Precision rate of 92.21%, Recall rate of 92.05% and F-measure rate of 91.97% for Case-1. The system achieves the average Precision rate of 91.56%, Recall rate of 91.42% and F-measure rate of 91.09% for Case-2. For both cases, the recognition performances are decreased due to similar shape of the sign ‘ফ’ with ‘ঝ’, ‘খ’ with ‘জ’, ‘ছ’ and ‘ঝ’, ‘ণ’ with ‘ধ’, ‘য়’, ‘দ’ and ‘ড়’ are shown in Fig.5.

Table 1. Result of BdSL Alphabet Signs Recognition

BdSL Alphabets	Precision (%)		Recall (%)		F-measure (%)	
	C1	C2	C1	C2	C1	C2
অ	90.57	94	96	95.92	95.48	94.95
আ	100	100	96	95.96	97.96	97.94
ই	97.94	96.91	95	94	96.45	95.43
উ	88.12	83.86	89	89	89.00	86.41
এ	86.54	87	91.84	88.78	89.11	87.88
ও	97.87	97.83	93.88	92.78	92	95.24
ক	94.85	92.91	92	92	93.40	92.46
খ	93.89	92.71	92	89	92.46	86.42
গ	94.34	94.23	100	100	94.34	92.45
ঘ	93.27	93.14	97	96.92	95.10	95
চ	97.89	96.84	93	92.93	95.38	94.85
ছ	86.54	84.62	90	88	88.23	86.27
জ	89.22	86.41	91	89.90	90.10	88.12
ঝ	80.91	76.31	89	87	84.76	81.31
ট	100	100	100	100	100	100
ঠ	100	100	100	100	100	100
ড	100	100	96	95.96	97.96	95.48
ঢ	95	94	95.96	95.92	95.48	94.95
ত	92.93	93.75	92	90.91	92.46	92.31
থ	100	100	93	93	96.37	96.37
দ	86.54	85.44	90	88	88.24	86.70
ধ	85.85	84.76	91	89	88.35	86.83
ণ	88.78	87.50	87	85.71	87.88	86.60
প	93.94	93.88	93	92	93.47	92.93
ফ	77.66	72.41	73	66.32	75.26	69.23
ব	100	100	98.99	98.99	99.49	99.49
ভ	100	100	95.96	96.94	97.94	98.45
ম	94.68	95.65	89	88.89	91.75	91.67
য়	86.14	85.29	87	88.78	86.57	87
র	72.16	71	70	72.45	71.10	71.72
ল	70.75	70.19	75	74.49	72.82	72.28
স	100	100	98	98	98.99	98.99
হ	100	99	100	100	100	99.50
ড়	90.29	93.68	93	90.82	91.63	92.22
ং	95	95	95	96.94	95	95.96
ঃ	97.94	97.92	95	95.92	96.45	95.91
Average	92.21	91.56	92.05	91.42	91.97	91.09
Mean System	91.89		91.74		91.53	

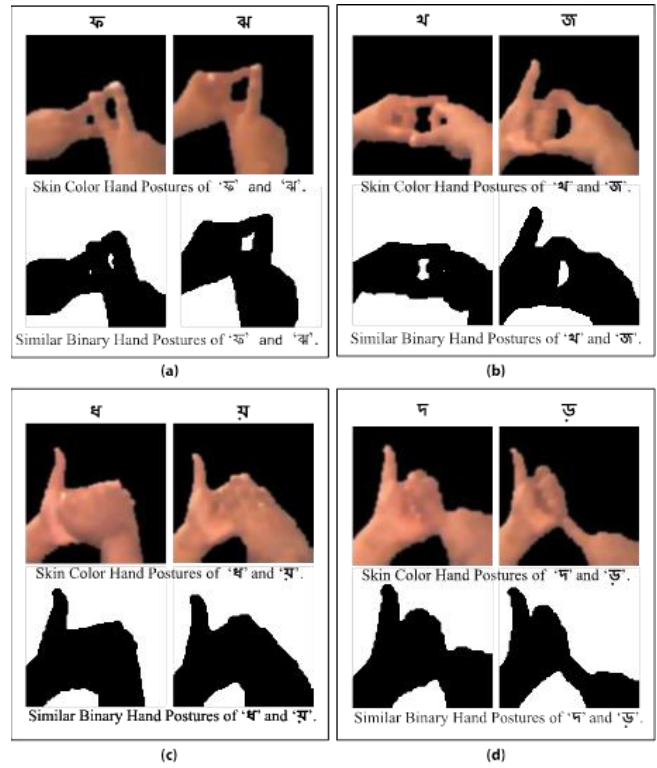


Fig. 5: Similarity of binary hand postures of Bengali consonant signs.

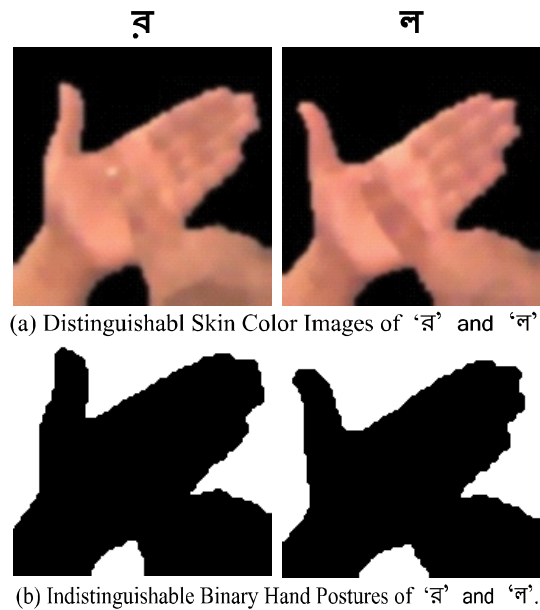


Fig. 6: Indistinguishable problem of binary hand postures 'র' with 'ল'.

F-measure rate of signs 'র' and 'ল' are decreased to less than about 72% and 73% respectively. Because, the skin color and grayscale hand postures of signs "র" and "ল" are distinguishable but the binary hand postures of them are very similar to each other as shown in Fig.6. In particular, performing the signs 'ও', 'খ', and 'জ' are most difficult in front of fixed camera which affects on recognition performances of the system.

Table 2 presents the summarized results of 10 Bengali numeral signs recognition considering both cases (C1 and C2). From the test results shown in Table 2, it is evident that Bengali numeral signs are recognized with the average Precision rate of 96.03%, Recall rate of 96.67% and F-measure rate of 96.92% for Case-1. The system achieves the average Precision rate of 96.41%, Recall rate of 96.39% and F-measure rate of 96.39% for Case-2. For both cases, the performance of one-handed Bengali numeral signs recognition is higher than the performance of two-handed BdSL alphabet signs recognition.

Table 2. Result of Bengali Numeral Signs Recognition

BdSL Numerals	Precision (%)		Recall (%)		F-measure (%)	
	C1	C2	C1	C2	C1	C2
০	94.95	95.96	95.92	95.96	95.43	95.96
১	100	100	100	100	100	100
২	97.98	96.04	97	97	97.49	96.52
৩	95	95.92	95	94	95	94.95
৪	98.95	96.91	94	94	96.41	95.43
৫	94.23	96.04	98.99	97	97.51	96.52
৬	94.12	94.17	96	97	96.97	95.57
৭	96.90	95.96	95.92	95.96	96.41	95.96
৮	93.20	94.17	96.97	97	95.50	95.57
৯	95	98.96	96.94	95.96	98.45	97.44
Average	96.03	96.41	96.67	96.39	96.92	96.39
Mean System	96.22		96.53		96.66	

Table 3. Result of Accuracy of BdSL Alphabets and Numerals Recognition

BdSL	Accuracy (%)		Mean System Accuracy (%)
	C1	C2	
Alphabets	92.04	91.41	91.73
Numerals	96.67	96.39	96.53
Average	94.36	93.90	94.13

Table 3 presents the Accuracy of BdSL alphabets and numerals recognition that are measured by putting the sum of total system's 'TP', total system's 'TN', total system's 'FP' and total system's 'FN' in Eq.(9) from the confusion matrixes considering both cases (C1 and C2). Mean Accuracies of the system are 91.73% for BdSL alphabets recognition and 96.53% for BdSL numeral signs recognition. The computational cost of the system is 88.09 milliseconds per frame which is calculated by Eq.(10).

Table 4 shows that the performances of the proposed system (BdSLR) are better than the existing reputed BdSL recognition systems. We have compared the test result of our proposed system with the test results of the systems represented by 'PCA', 'Haar-KNN' and 'ANN' including preprocessing, segmentation, feature extraction, training and classification of the mentioned systems; not only with different method or classifier such as PCA, Haar-KNN and ANN. We have implemented those systems using same dataset of our proposed system (BdSLR) considering only Case-1 (C1).

Table 4. Comparative analysis of the results of our proposed system (BdSLR) with the system 'PCA', 'Haar-KNN' and 'ANN' for mean system Accuracy and computational cost

BdSL	Accuracy (%)				Computational Cost (Milliseconds/frame)			
	BdSL R	PCA [1]	Haar-KNN [15]	ANN [13]	BdSL R	PCA [1]	Haar-KNN [15]	ANN [13]
Alphabets	92.04	89.55	80.07	87.99	89.14	121.45	78.11	112.33
Numerals	96.67	92.01	95.08	90.57	87.03	120.77	78.05	112.17
Mean System	94.36	90.78	87.58	89.28	88.09	121.11	78.08	112.25

Especially by using Haar cascade classifier and skin color segmentation method in combination, the proposed system performs robustly under various illumination and backgrounds than the other mentioned systems. Fig.7 shows the example snapshots of hand postures recognition of BdSL in various illumination and cluttered background robustly.



Fig. 7: Example snapshots of successfully recognition of hand postures of BdSL in various illumination and cluttered background.

4. Conclusion

This paper presents a real-time appearance-based Bengali alphabet and numeral signs recognition system. Haar cascade classifiers are used to detect the predefined hand posture from the captured image to define the ROI. Skin color-based segmentation method is used to segment probable hand postures from the ROI and the segmented images are converted to binary images. After resizing the binary images, the system generates the feature vector for

each of the resized binary image which will be used for training and/or testing process. KNN classifier is used to recognize Bengali alphabet and numeral signs. The system is trained separately using 3600 (36×10×10) hand postures for 36 Bengali alphabet signs and 1000 (10×10×10) hand postures of 10 Bengali numeral signs from 10 performers. The system is tested 7200 hand postures of 36 alphabet signs and 2000 hand postures of 10 numerals where 3600 images of alphabet signs and 1000 images of numeral signs are captured from the performers who didn't participate in training process. The system achieves the average Accuracy of 92.04% for BdSL alphabets recognition and 96.67% for BdSL numerals recognition from the 10 trained performers. The system achieves the average Accuracy of 91.41% for BdSL alphabets recognition and 96.39% for BdSL numerals recognition from another 10 non-trained performers. The recognition Accuracies for non-trained performers are slightly lower than the trained performers but still satisfactory. The computational cost of the system is 88.09 milliseconds per frame which makes the system real-time with satisfactory Accuracies. The performances of the system for Bengali One-Handed numeral sign recognition are higher than the recognition of two-handed alphabets of BdSL. The system is capable of recognizing any static signs of any sign language in illumination variation and cluttered background, if those signs are trained properly. However the system has a few limitations. The system cannot properly segment hand postures if some objects rather than hand have skin like colors within the ROI. Sometimes the system fails to classify properly among similar binary signs as shown in Fig.5 and Fig.6 which are indicated to improve in future research. The system is applicable to assist as an interpreter for sign and non-sign people communication using BdSL.

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References

1. Begum, S., Hasanuzzaman, M., 2009, "Computer vision-based Bangladeshi Sign Language recognition system". In: 12th ICCIT- 2009 Dhaka, Bangladesh, pp. 414-419.
2. Bangladesh Sign Language Committee, 1994, "Bengali Sign Language Dictionary" Dhaka, Bangladesh.
3. Kulkarni, V. S., Lokhande, S. D., 2010, "Appearance Based Recognition of American Sign", In: International Journal on Computer Science and Engineering (IJCSE), vol. 02(03), pp. 560-565.
4. Ong, E., Cooper, H., Pugeault, N., Bowden, R., 2012, "Sign language recognition using sequential pattern trees", In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Providence, RI, pp. 2200 – 2207.
5. Naoum, R., Owaied, H. H., Joudeh, S., 2012, "Development of a new Arabic Sign Language recognition using K-Nearest Neighbor algorithm", In: Journal of Emerging Trends in Computing and Information Sciences, vol. 3(8) p.1173-1178.
6. Sako, S., Kitamura, T., 2013, "Subunit Modeling for Japanese Sign Language Recognition Based on Phonetically Depend Multi-stream Hidden Markov Models", In: Universal Access in Human-Computer Interaction. Design Methods, Tools, and Interaction Techniques for eInclusion, Springer, Berlin Heidelberg, pp.548-555.
7. Holden, E., Lee, G., Owens, R., 2005, "Automatic Recognition of Colloquial Australian Sign Language", In: Proceedings of the IEEE Workshop on Motion and Video Computing (WACV/MOTION'05), Breckenridge, CO, pp.183-188.
8. Eshaque, A., Hamid, T., Rahman S., Rokonuzzaman, M., 2002, "A Novel Concept of 3D Animation Based 'Intelligent Assistant' for Deaf People: for Understanding Bengali Expressions", In: Proceedings of the 5th ICCIT-2002, Dhaka, Bangladesh, pp.252-256.
9. Pavel, D. S. H., Mustafiz, T., Sarkar, A.I., Rokonuzzaman, M., 2004, "Modeling of Bengali Sign Language expression as dynamic 3D polygons for developing a vision based intelligent system for dumb people", In: National Conference on Computer Processing of Bangla, Independent University, Bangladesh.
10. Pavel, D. S. H., Mustafiz, T., Sarkar, A.I., Rokonuzzaman, M., 2003, "Geometrical Model Based Hand Gesture Recognition for Interpreting Bengali Sign Language Using Computer Vision", In: proceedings of the 6th International Conference on Computer & Information Technology (ICCIT-2003), Dhaka, Bangladesh, pp.642-647.
11. Rahim, F. M., Mursalin, T. E., Sultana, N., 2008, "Intelligent Sign Language Verification System– Using Image Processing, Clustering and Neural Network Concepts." In: American International University, and University Of Liberal Arts, Bangladesh.
12. Deb, K., Mony, H. P., Chowdhury, S., 2012, "Two-Handed Sign Language Recognition for Bangla Character Using Normalized Cross Correlation", In: Global Journal of Computer Science and Technology (GJCST), vol. 12(3), Version 1.0.
13. Rahman, M. A., Ahsan-Ul-Ambia, Abdullah, M. I., Mondal, S. K., 2012, "Recognition of static hand gestures of alphabet in Bangla Sign Language", In: IOSR Journal of Computer Engineering (IOSRJCE), vol. 8(1), pp.07-13.
14. Karmokar, B. C., Alam, K. M. R., Siddiquee, M. K., 2012, "Bangladeshi Sign Language Recognition employing Neural Network Ensemble", In: International Journal of Computer Applications (IJCA), vol.58(16).

15. Jasim, M., Zhang, T., Hasanuzzaman, M., 2014, "A real-time computer vision-based static and dynamic hand gesture recognition system", In: International Journal on Image and Graphics, vol. 14(01n02).
16. Rahaman, M. A., Jasim, M., Ali, M. H., Hasanuzzaman, M., 2014, "Real-Time Computer Vision-Based Bengali Sign Language Recognition", In: Proceedings of the 17th Int'l Conf. on Computer and Information Technology (ICCIT), pp.192-197.
17. Ismail, W. N. W., 2009, "Object detection system using Haar-Classifer", In: Faculty of Electrical & Electronics Engineering, University Malaysia Pahang.
18. Phung, S. L., Bouzerdoum, A., Chai, D., 2005: Skin Segmentation Using Color Pixel Classification: Analysis and Comparison", In: IEEE transactions on pattern analysis and machine intelligence, vol. 27(1), pp.148-154.
19. Gonzalez, R. C., Woods, R. E., 2006, "Digital Image Processing, (3rd Edition), Prentice-Hall, Inc., Upper Saddle River, NJ, USA.
20. Sharma, R., Nemani, Y., Kumar, S., Kane, L., Khanna, P., 2013, "Recognition of Single Handed Sign Language Gestures using Contour Tracing Descriptor", In: Proceedings of the World Congress on Engineering (WCE), London, U.K., vol.2, pp.754-758.
21. <http://sourceforge.net/projects/emgucv/files/latest/download> Accessed at 08/04/2013.
22. Nagarajan, S., Subashini, T.S., 2013, "Static Hand Gesture Recognition for Sign Language Alphabets using Edge Oriented Histogram and Multi Class SVM" In: International Journal of Computer Applications, vol. 82(4), pp.28-35.