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Effects of Different Color Models in Hand Gesture Recognition

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Abstract

Objectives: This paper presents a comparative analysis between different color models (YCrCb, YUV, HSV, CIE L*a*b*, and CIE L*u*v*) for hand gesture recognition task by extracting skin-color of index 31-35 on Von Luschan's chromatic scale. **Methods/Statistical Analysis:** An eight step algorithm is proposed for comparing different color models, which is simple so as to run in real-time and is kept same for all the color models. Only the threshold for extracting skin-color is different for all the color models to extract the desired region. Morphology operations are used to remove noise and Contour and Convex Hull technique is used to extract desired features. Test data was generated using 16 users and each user performed 2 sequences of 6 different gestures for every color model giving a total of 5760 test data points. Accuracy Percentage, False Positive Rate (FPR) and True Positive Rate (TPR) are used to evaluate color models. **Findings:** Since the options are several, it becomes crucial which color space to use. In this paper, we have analyzed which color space can most accurately preserve the hand shape and recognize it for skin color of index 31-35 on Von Luschan's chromatic scale. Experimental results have shown that the CIE L*a*b* and YCrCb color space are the most versatile in different environment settings with 73.9% and 71.5% accuracy, respectively. CIE L*a*b* and CIE L*u*v* are found to have highest TPR and HSV had lowest FPR. Whereas YCrCb and YUV are better than HSV in terms of TPR and not so good compared to CIE L*a*b* and CIE L*u*v*. Also YCrCb and YUV have lesser FPR than CIE L*a*b* and CIE L*u*v* but higher than HSV. These findings will help the researchers of the field of Human-Computer Interaction to select appropriate color-model for specific applications. This paper proposed an algorithm that can be improved to include complex gestures for evaluation. **Improvements:** Algorithm developed for evaluation can be modified to use machine learning techniques to allow complex gestures and can be accommodated according to different color models. Also other color models can also be included to perform exhaustive evaluation.

Keywords: Color Models, Color Spaces, Hand Gesture Recognition, Human Computer Interaction, Skin-Color

1. Introduction

Computer technologies have grown tremendously to an extent that interacting with the computing devices has become a necessity[1]. Existing techniques of user input such as a mouse, keyboard or touch screen are becoming bottlenecks in the effective interaction with the available information flow as the communication and display technologies progress further[1,2]. These techniques of user input are less natural and intuitive[2]. While humans communicate verbally; gesture and vision is also of great importance to get information. A gesture or pose, unlike face to face communication, is a type of interaction correspondence made by the parts of the body[3].A great deal of technological development is going on in the field of computer-vision[1,4-9] which inspire to develop more natural and intuitive human-computer interface. Computer vision has an advantage that usually lesser effort than for other sensors is needed for users to get comfortable interacting with the system. But it has a major problem of reliable image analysis in different illumination settings and with different skin-tone users[10].

Computer Vision-based systems works in three-phases: Detection, Tracking, and Recognition[1]. In the first phase for hand detection, several techniques can be found in [11]among which, skin-tone or skin-color segmentation

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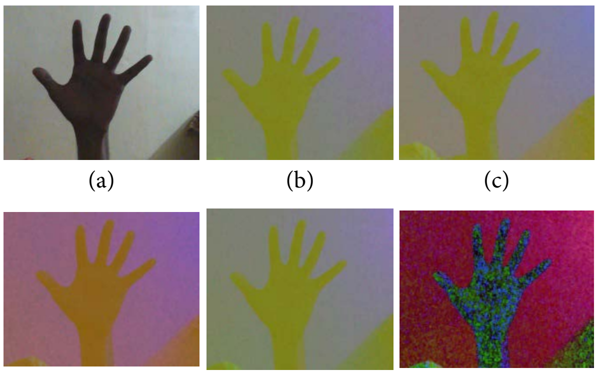
approach has been utilized by[2,8,10,12-15] and many others. For accurate skin-color detection, the color spaces that can efficiently separate chromaticity from the luminance components are used as it will provide some robustness to the illumination changes. Figure 1, for a given RGB image its equivalent image in different color model is shown.



(a) (b) (c)

(d) (e) (f)

Figure 1. Original Image (a) in different color space shown in - (b) YCrCb (c) Lab (d) Luv (e) YUV (f) HSV.

In[2,8,12-15] and several others have selected a color model for skin color extraction based on the studies presented in[16-19]. In[16], all the previous work on extracting skin-color was compared on factors of color model and classification approach used. Also, a comparative analysis was done on several color models using different classification techniques for modeling human skin color which gave the best skin detection performance in HSI color space[16].

In[17], YCrCb color space was deemed most appropriate for modeling human skin color on the factors of its applicability and effectiveness. It was also hypothesize that a skin-color model can remain effective regardless of varying skin-color if the color space is independent of the luminance of the image[17].

A hybrid approach was presented in[18], in which RGB, YCrCb, and HSI color models were used together and the resultant binary image of each of these color spaces were merged to get the final result which has segmented skin-color. This algorithm was used to detect the face in a given image and the approach has achieved the accuracy of 95.18% but could not work in real time[18].

Chromaticity is an objective specification of the quality of color with reference to its purity and its dominant wavelength[20], whereas Luminance is a measure of brightness per unit area of radiating surface in candela per square meter (nits)[21]. Thus, the color spaces that efficiently demarcate chromaticity from luminance are robust to illumination variations[18].

In this paper, the effects of different color models are compared when used in hand gesture recognition by modeling human skin color. This could be done for object tracking but it is of importance and more interesting to find which color model can most accurately preserve the actual hand shape in threshold image. For comparison, YCrCb, YUV, HSV, CIE L*a*b*, and CIE L*u*v* color models are selected, where YCrCb and YUV are of same family and CIE L*a*b* and CIE L*u*v* are of same family. Experiments have been performed to find the most suitable color model for varying illumination and background situations that can most accurately preserve hand shape to recognize gestures made.

The rest of the paper is organized as follows. In Section 2, different environment settings and conditions under which the system was tested are defined and also describes the gesture to be detected. Section 3 introduces and explains the algorithm used for the experimentation and also defines the threshold range for skin-color extraction for different color spaces. In Section 4, we discuss the implementation technology and the inferences made from the obtained results. Section 5, finally summarizes the paper.

2. Definitions and Conditions

2.1 Environment Settings

Six settings are defined under which this experiment was performed using following environment factors: Simple Background (SB), Complex Background (CB), Bright Lighting (BL), Moderate Lighting (ML), and Dim Lighting (DL). Here, each term is defined as follows: In Simple Background, the object to be tracked (in this case, hand) is over the color unvarying background i.e. it is of one simple color. The background where color is varying highly is Complex Background. Bright Lighting is defined as where light comes from multitude of sources and hence not causing shading or shadow effects. This also includes light sources such as sunlight. Moderately lighted room is in which there is some shadowing effect but light sources are sufficient to illuminate the room completely. Dim lighting conditions are where there are few light sources and varying shading.

Thus, the six environment settings are obtained by pairing background environment factor with lighting environment factor. These are: SBBL, SBML, SBDL, CBBL, CBML, and CBDL. SBBL means that the experiment was conducted under simple background and in highly illuminated room. SBML is the environment setting in which background was simple and moderate light setting was present in the room. In SBDL, the environment had simple background and dim lighting conditions. Similarly, CBBL is for the complex background and illuminated room. CBML means complex background and moderate lighting. And, CBDL is the environment where the background was complex with dim lighting conditions.

2.2 Gestures

To validate the system, it is required to correctly count the number of fingers elevated. Hence, the gestures used in this system correspond to the numbers zero to five. It is essential that the fingers are spaced enough for the system to identify the correct gesture. Gestures that can be recognized by the system are shown in Figure 2.

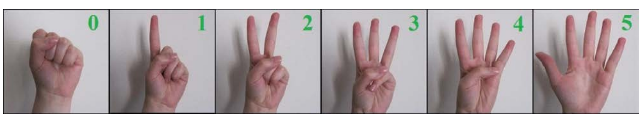


Figure 2. Gestures Used In Our System that Correspond to Numbers Zero to Five.

Note that it doesn't matter which finger is elevated, the system should count the number of fingers elevated.

3. Methodology

3.1 Algorithm

For proper evaluation of effects of different color models in the task of hand gesture recognition using skin-color extraction approach, the algorithm should be simple so that it can run in real time and it should be same for comparing all color models. Hence, following algorithm is proposed as shown in Figure 3:

- Input Frame: In this step, image frames are read from the camera at 30-60 frames per second (depending on the camera) and Gaussian smoothing is applied before passing these frames to the next step. Frames are then sent to two different stages: one for background subtraction and another for color space conversion. The insight behind sending the same image to two different disconnected stages here is that the background subtraction can extract the varying foreground that might contain noise of unwanted objects which will be filtered in steps 3 and 4 of the algorithm. And the noise arising from color filtering (i.e. in steps 3 and 4) will be cleared in by background subtraction (i.e. in step 2).
- Background subtraction: In this step, absolute difference between the current frame and the previously stored background image is being taken in BGR color space and is converted to a binary image. Resultant image of this step may contain some unwanted noise in the extracted foreground which may not have the expected color to be tracked.
- Convert to C_i: Received frames are converted to a color model C_i in each experimental run, where C_i could be either of YCrCb, HSV, CIE L*a*b*, CIE L*u*v*, and YUV color model.
- Thresholding and Binarization: Thresholding is applied in both the stages to retrieve the desired Region of Interest (ROI) and then converted to a binary image using (Equation - 1).

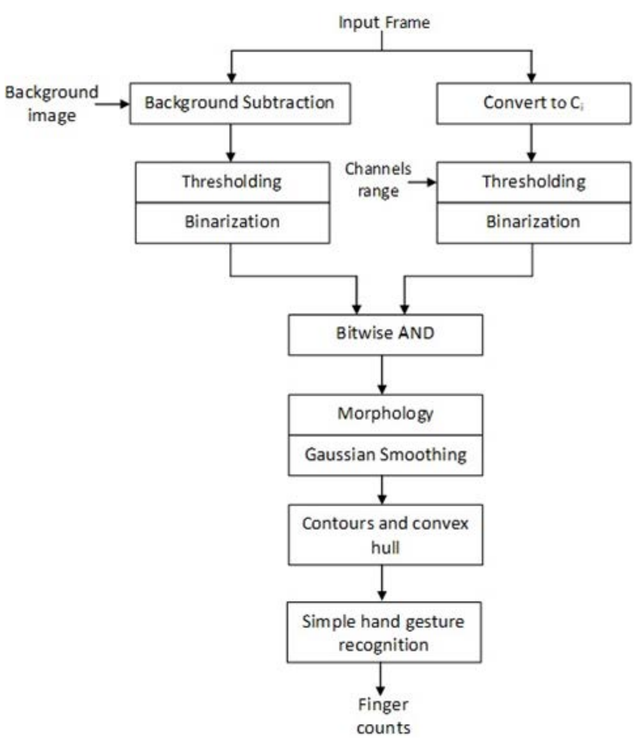


Figure 3. Proposed Algorithm.

$$d(x,y) = \begin{cases} 1, & s(x,y) > thresh \\ 0, & otherwise \end{cases} \tag{1}$$

Threshold range has been defined in (Equation 2) and in (Equation3) for different channels of the mentioned color models. These values have been determined after thorough experimentation by recording values for skin-color extraction of different skin-color users from Indian subcontinent and then taking the average of these values.

$$33 < Y < 111$$
$$126 < Cr < 154$$
$$112 < Cb < 141 \qquad \ldots(2\text{-a})$$

$$34 < Y < 111$$
$$127 < U < 156$$
$$113 < V < 142 \qquad \ldots(2\text{-b})$$

$$0 < H < 128$$
$$29 < S < 119$$
$$41 < V < 115 \qquad \ldots(2\text{-c})$$

$$13 < L < 46$$
$$-7 < a < 24$$
$$-8 < b < 21 \qquad \ldots(2\text{-d})$$

$$13 < L < 48$$
$$-26 < u < -3$$
$$0 < v < 19 \qquad \ldots(2\text{-e})$$

$$165 < Y < 255$$
$$125 < Cr < 162$$
$$101 < Cb < 134 \qquad \ldots(3\text{-a})$$

$$132 < Y < 255$$
$$114 < U < 199$$
$$71 < V < 162 \qquad \ldots(3\text{-b})$$

$$0 < H < 47$$
$$22 < S < 148$$
$$141 < V < 255 \qquad \ldots(3\text{-c})$$

$$56 < L < 100$$
$$-18 < a < 46$$
$$0 < b < 76 \qquad \ldots(3\text{-d})$$

$$60 < L < 100$$
$$-37 < u < 4$$
$$3 < v < 45 \qquad \ldots(3\text{-e})$$

Since the system is tested in both room illumination settings and in under sunlight settings, each threshold value was set in each test run for the respective color model as mentioned in (Equation 2) for room illumination settings and values mentioned in (Equation 3) under sunlight settings.

- Bitwise AND: Resultant binary images from both background subtraction module and filtered color space are then merged by using bitwise AND operator. Noise from both the phases is removed by this operation as noise of one phase didn't exist in another unless it exist in both. Such noise is due to skin-colored object existing in the foreground image also.
- Morphology: To effectively remove the noise from the binary image, morphology opening operation (erosion followed by dilation) is applied. Erosion suppresses small spike noises (i.e. small unwarranted bright regions) but it also shrink the desired object, so dilation is applied to enlarge the desired object [22]. After that, Gaussian blurring to smooth the boundary has been employed.
- Contour and convex hull: For comprehending the complex shape of hand, a convex hull is computed and then its convexity defects are found[22,23]. Such defects can very well characterize the shape of complex objects like hands.
- Simple hand gesture recognition: Using convex hull and convexity defects found in step-7 are then used to detect the finger tips and and recognize if it is folded or not.

The system was able to count the number of fingers at step-8 using all the information obtained from previous steps. Figure 4, output of algorithm's step-1 to 7 is shown and inFigure 5, output of the step 8 is shown.

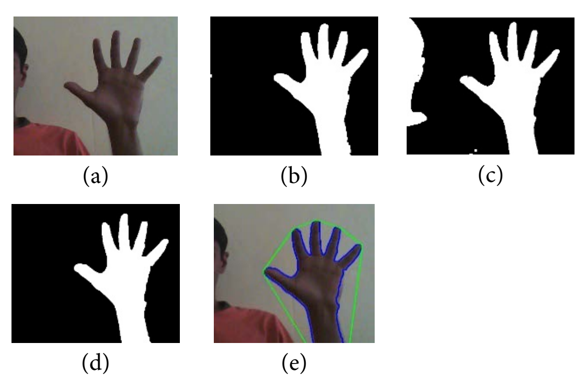
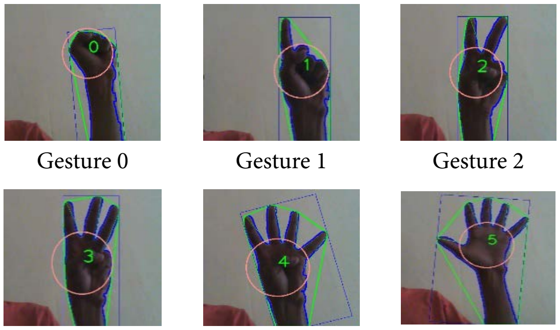


Figure 4. Output of the Algorithm at Each Step.



Gesture 0 Gesture 1 Gesture 2

Gesture 3 Gesture 4 Gesture 5

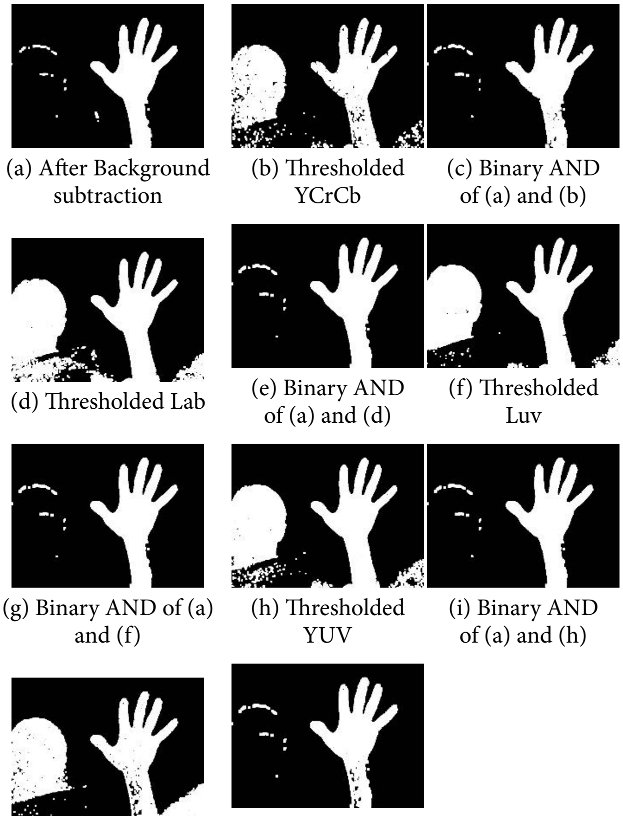
Figure 5. Gesture Recognition at step 8) of the Algorithm.

Result of Bitwise AND of background subtracted image and threshold image of different color models is shown in Figure 6. Background subtracted binary image is shown in Figure 6-a and Figure 6-b, Figure 6-d, Figure 6-f, Figure 6-h, and Figure 6-j are the image extracted from color space YCrCb, Lab, Luv, YUV, and HSV, respectively, after applying threshold mentioned in (Equation 2). Figure 6-c, Figure 6-e, Figure 6-g, Figure 6-i, and Figure 6-k are the result of performing binary AND on Figure 6-a and Figure 6-b, Figure 6-a and Figure 6-d, Figure 6-a and Figure 6-f, Figure 6-a and Figure 6-h, and Figure 6-a and Figure 6-j, respectively.

	1	10			19	28	
	2	11			20	29	
	3	12			21	30	
	4	13			22	31	
	5	14			23	32	
	6	15			24	33	
	7	16			25	34	
	8	17			26	35	
	9	18			27	36	

Figure 6. Von Luschan's Chromatic Scale.

After applying the threshold as mentioned in (Equation 2) on the Von Luschan's chromatic scale as shown in Figure 7[24], it is found that the skin index on which the system was tested is in range 31-35 in all of the illumination settings including indoor bright light, except extreme bright i.e. in sunlight condition. In extreme bright setting the scale was found out to be in 1-14 with the threshold mentioned in (Equation 3). In extreme bright conditions the threshold settings used for indoor conditions failed due to abrupt change in the luminance channel and hence skin color could not be extracted. The thresholds mentioned in (Equation 3) are applicable in this environment.



(a) After Background subtraction (b) Thresholded YCrCb (c) Binary AND of (a) and (b)

(d) Thresholded Lab (e) Binary AND of (a) and (d) (f) Thresholded Luv

(g) Binary AND of (a) and (f) (h) Thresholded YUV (i) Binary AND of (a) and (h)

(j) Thresholded HSV (k) Binary AND of (a) and (j)

Figure 7. Binary Images Obtained at from Steps 2) to 6) of the Algorithm for Different Color Models.

4. Experimentation

4.1 Test Data

The system was evaluated with sixteen users for each of the five color models and six environment settings; each user performed two sequences of gesture where each sequence was of six gestures (in random order) taken from the defined gesture set. Therefore, each user made 360 gestures, giving us a test data set of 5760 gestures.

4.2 Implementation

The algorithm was implemented in C++ using Open CV framework on a notebook running 2.50GHz dual-core processor with 4GB of RAM and having a webcam of 1.3MP capturing frames on resolution of 640 × 480.

4.3 Results and Discussion

Figure 8 shows some of the screenshots of the working of system in different environment settings. The accuracy results of gesture recognition for the "YCrCb" color space can be seen in Table 1. Similarly, in Table 2, Table 3, Table 4, and Table 5 the accuracy results of gesture recognition are shown for color models "YUV", "HSV", "CIE L*a*b*", and "CIE L*u*v*", respectively.

Figure 8. Output (both correct and incorrect results) in a Sample Run of the System.

Table 1. Test Results for "YCrCb" Color space

Gesture Detected	Test Environment						Overall Correct
	SB BL	SB ML	SB DL	CB BL	CB ML	CB DL	
0	30	32	32	29	30	29	182/192
1	23	27	27	13	17	18	125/192
2	17	23	23	11	15	13	102/192
3	17	21	22	9	16	15	100/192
4	28	28	28	22	21	22	149/192
5	29	30	30	25	27	25	166/192
Accuracy (%)	75.0	83.9	84.4	56.8	65.6	63.5	71.5

Table 2. Test Results for "YUV" Color space

Gesture Detected	Test Environment						Overall Correct
	SB BL	SB ML	SB DL	CB BL	CB ML	CB DL	
0	30	32	32	23	27	26	170/192
1	23	26	27	13	15	15	119/192
2	13	25	25	10	14	13	100/192
3	14	24	22	11	16	13	100/192
4	24	26	24	24	21	22	141/192
5	30	29	24	24	26	23	156/192
Accuracy (%)	69.8	84.4	80.2	54.7	62.0	58.3	68.2

Table 3. Test Results for "HSV" Color space

Gesture Detected	Test Environment						Overall Correct
	SB BL	SB ML	SB DL	CB BL	CB ML	CB DL	
0	23	31	28	19	21	21	143/192
1	14	20	19	11	13	14	91/192
2	11	18	16	9	10	10	74/192
3	12	18	18	10	10	11	79/192
4	19	21	21	17	18	17	113/192
5	21	29	27	20	19	17	133/192
Accuracy (%)	52.1	71.4	67.2	44.8	47.4	46.9	54.9

Table 4. Test Results for "CIE L*a*b*" Color space

Gesture Detected	Test Environment						Overall Correct
	SB BL	SB ML	SB DL	CB BL	CB ML	CB DL	
0	31	32	32	30	32	31	188/192
1	27	29	29	14	16	16	131/192
2	21	27	26	12	12	12	110/192
3	20	27	27	13	12	13	112/192
4	29	29	27	20	25	22	152/192
5	30	31	29	20	26	21	157/192
Accuracy (%)	82.3	91.2	88.5	56.8	64.1	59.9	73.9

Table 5. Test Results for "CIE L*u*v*" Color space

Gesture Detected	Test Environment						Overall Correct
	SB BL	SB ML	SB DL	CB BL	CB ML	CB DL	
0	29	30	30	24	26	26	165/192
1	27	28	27	12	14	13	121/192
2	24	24	24	11	12	12	107/192
3	21	23	24	11	12	12	103/192
4	26	27	27	20	22	23	145/192
5	27	27	27	20	26	25	152/192
Accuracy (%)	80.2	82.8	82.8	51.1	52.1	57.8	68.8

While testing the system in extreme bright settings, threshold range defined in (Equation 2) for all the color models were changed for the luminance channel to accommodate as per the illumination. Updated threshold ranges were shown in (Equation 3). However, in the chromaticity channels there was a small change observed in the threshold.

Results have shown that CIE L*a*b* has the highest hand gesture recognition accuracy as demarcating luminance from chrominance is much more effective in it. Much closer results to it were produced by using YCrCb. High accuracy results were obtained for these two color models because these could extract the desired object without affecting its shape much. In Simple Background conditions, CIE L*a*b* has produced highest accuracy and consistent results, whereas in the Complex Background conditions YCrCb did much better. HSV could not perform better in all the cases due to its inability to maintain the depth information, especially around the brightest part of the image.

We have also evaluated our work on the following metrics[25] as mentioned in (Equation 4) and (Equation 5): False Positive Rate (FPR) and True Positive Rate (TPR).

$$FPR = \frac{\text{No.of non-skin pixel classified as skin}}{\text{Total no. of non-skin pixel}} \quad (4)$$

$$TPR = \frac{\text{No. of skin pixel correctly classified}}{\text{Total no. of skin pixel}} \quad (5)$$

FPR and TPR as shown in Table 6 for all color models are calculated by comparing the threshold image obtained at step 6) of the algorithm with the ground truth image pixel wise. As per the results, HSV color model had the least FPR but also it compromised with the TPR, and hence required more dilation operation compared to other color models used in this experiment. CIE L*a*b* and CIE L*u*v* had the highest TPR but also the highest FPR. YCrCb had smaller TPR than CIE L*a*b* but much better than HSV and lower FPR than CIE L*a*b* and much closer to HSV.

Table 6. TPR and FPR for different color models

Color Models	TPR (%)	FPR (%)
HSV	66.2	3.41
CIE L*a*b*	98.27	9.19
CIE L*u*v*	98.3	9.23
YCrCb	89.1	6.72
YUV	87.98	6.83

5. Conclusion

In this paper, several color spaces that are most frequently used in skin-color extraction for Hand gesture recognition are compared. The results have shown that for hand gesture recognition CIE L*a*b* and YCrCb performed better not just in controlled environment settings but also in varying illumination and background. However, CIE L*a*b* color space gave overall highest accuracy results compared to all others.

Concluding that both CIE L*a*b* and YCrCb should be preferred due to the ability of effectively separating the brightness from the color channels that increases the likelihood of extracting the targeted object while preserving its geometric properties which results in high hand gesture recognition accuracy, and TPR and lower FPR. Results have shown that CIE L*u*v* has higher TPR and FPR as mentioned in table 6, but hand gesture recognition accuracy is not much.

HSV requires more morphological operations compared to other color models used for comparison in this paper so as to recover shape of the extracted object. This happens because of its inability to maintain the depth information, especially around the brightest part of the image.

Also, different color models can produce different results in varying settings and for different algorithms used. We have proposed the simplest algorithm for the comparison but different algorithms and operations can improve the results of some particular color space and at the same time can reduce the performance when used others.

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