ESKİŞEHİR TEKNİK ÜNİVERSİTESİ BİLİM VE TEKNOLOJİ DERGİSİ
B- TEORİK BİLİMLER

Eskişehir Technical University Journal of Science and Technology B- Theoretical Sciences

Internatıonal Conference on Natural Sciences and Technologies
Iconat Special Issue 2021

2021, Vol:9, pp. 61-64, DOI: 10.20290/estubtdb.1011578

REAL-TIME SKIN SEGMENTATION ON LOW RESOLUTION AND GRAY IMAGES

Utku KAYA [1,*], Abidin KILIÇ [2]

[1] Vocational School of Transportation, Eskişehir Technical University Eskisehir, Turkey
[2] Department of Physics, Eskişehir Technical University Eskisehir, Turkey

ABSTRACT

In this study, the skin segmentation problem, which is frequently used in the literature, will be detected on a real-time webcam with semantic segmentation deep learning algorithms. Skin segmentation generally requires high processing power to distinguish it from images with high resolution. The deep learning algorithm and the proposed image processing method used in this study provide real-time, very low CPU usage, and lag-free skin detection via webcam.

Keywords: Skin segmentation, Deep learning, Semantic segmentation

1. INTRODUCTION

Skin detection has been an interesting and challenging topic for researchers. Skin detection has many working areas. Especially hand and face tracking, sign language, communication between humans and computers, and filtering adult pictures. The reason why skin segmentation is a challenging and interesting topic is that there are multiple differences in the images to be distinguished. Each image features multiple different external conditions, such as people of different races, different lighting conditions, colors like human skin, hue, and saturation. Under the influence of such external factors, successful skin segmentation has attracted the attention of researchers [1-5].

For skin detection, researchers have been working on classical machine learning for a long time [6-9]. The main disadvantage in machine learning is the feature extraction process. Extracting the features of millions of pixels and processing these features requires high processing power and time. In addition, it is not guaranteed that every feature purposed in the literature will increase the success of skin segmentation. Using extra features or combining them increases the success as well as decreases it. At the same time, algorithms trained with so many features have difficulty in real-time, without lags and a high-resolution skin segmentation process.

Deep learning is a type of machine learning, which is a subset of artificial intelligence. However the biggest advantage of deep learning algorithms is that the human factor effect is quite low. In particular, the importance of training the network without extracting the attribute of each pixel is undeniable. In addition, to detect skin in images that are not in the data set, extracting the features of each image and detecting it with machine learning requires serious processing power. This makes real-time (from the camera) skin detection extremely difficult.

2. METHODS

In this study, a semantic segmentation network will be trained using the Pratheepan dataset [10]. There are a total of 78 images in dataset. These images also include ground truth images. Since we are detecting

*Corresponding Author: utkukaya@eskisehir.edu.tr
Received: 18.10.2021 Published: 24.12.2021

with a deep learning network, there is no need to extract the features of each pixel. The purposed semantic segmentation network is used as in Figure 1..

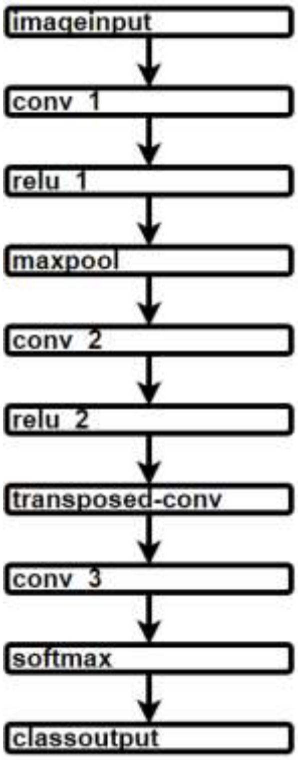

Figure 1. Purposed semantic segmentation network.

A striking point in this study is to train the network by lowering the resolution of the images. It is better to train the network with high-resolution images, but our main goal is to prove the success of the deep learning network even under the most difficult conditions. At the same time, images will be converted to the gray format. Even if this makes detection very difficult, it will make it easier to process data from the real-time camera and reduce delays.

Real-time camera images are shown in Figure 2. The resolution of the camera is adjusted as 320x240. Images are taken randomly without editing in the captured environment. These images are taken in real-time with converting gray format as seen a and b images in Figure 2.

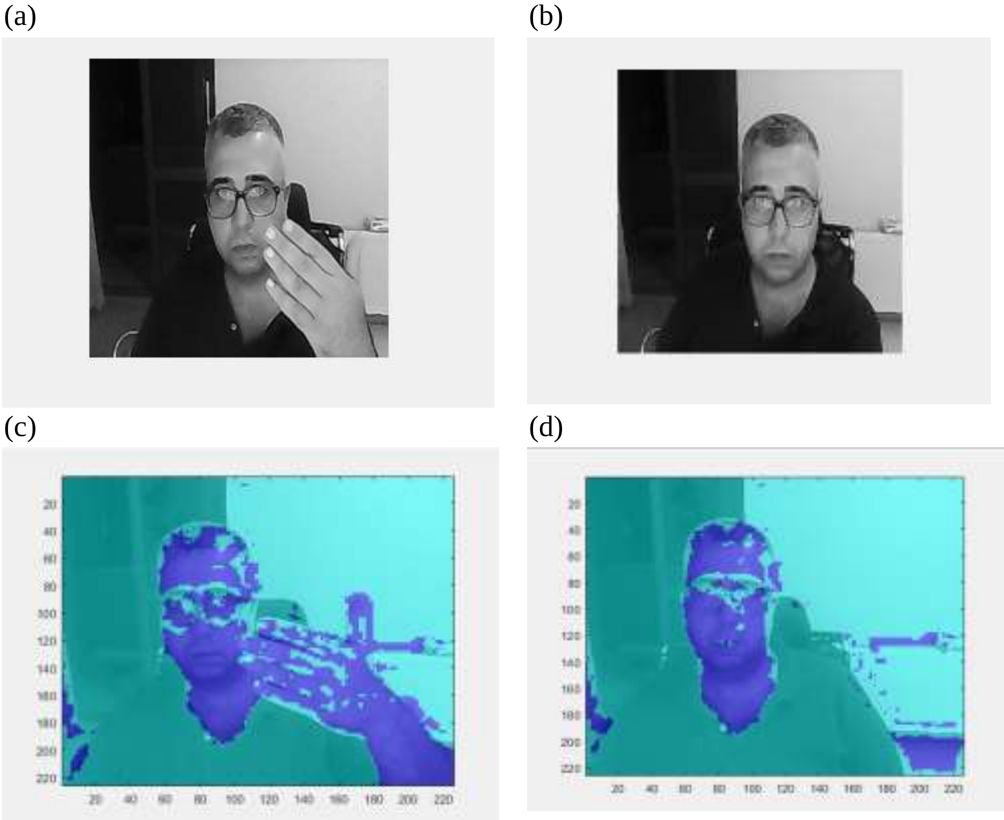

Figure 2. Real-time camera images of the author (a, b=input camera view, c, d=after skin detection process)

When looking at the webcam images (c and d) the green parts show nonskin pixels and the blue parts are skin pixels. Even in very low-resolution camera images, skin detection is made very easily. Even glasses are detected as nonskin. In figure 2 image c, it is determined that the hand of the author as skin. It is normal for some background images to be detected as non-skin. Because the resolution of the camera is set too low, and the ambient light is not properly adjusted.

Table 1. Execution time of purposed real-time skin segmentation.

	Min	Max	Mean
Execution time(second)	0.0231	0.1460	0.1318

Another remarkable point in this study is the detection time. Skin segmentation was performed by taking 100 samples from the camera image. Skin segmentation time is reduced to 0.0231 seconds. The maximum detection time is 0.1318 sec. The average time is 0.1318 sec. As it is understood from these results, it is possible to detect the skin in real-time without delay.

Table 2. Normalized Confusion matrix

Confusion Matrix		
Skin	87.55	12.45
Nonskin	30.3	69.7
	Skin	Nonskin

The average success values of the algorithm taken from different frames are given in the confusion matrix. 87.55% of the skin pixels were identified as skin. On the other hand, 69.7% of nonskin pixels were detected as nonskin. Our network is trained by low-resolution, gray images. Therefore, these results are acceptable for real-time image detection.

CONCLUSION

The main purpose of this study is to make skin segmentation from low-resolution gray images. A simple deep learning algorithm is used for this. It has been demonstrated that skin segmentation can be performed on a superior and real-time camera even without any feature extraction and in the absence of color space. The RGB attributes of the images have been eliminated, and the camera resolution has been kept very low. even though the number of images used for training is very small for a deep learning application (78 in total). The purposed network has made a very successful and real-time detection.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

REFERENCES

[1] Phung Son Lam, Abdesselam Bouzerdoum and Douglas Chai. Skin segmentation using color pixel classification: analysis and comparison. IEEE transactions on pattern analysis and machine intelligence, 2005; 27.1 148-154.

[2] Phung Son Lam, Douglas Chai and Abdesselam Bouzerdoum. Adaptive skin segmentation in color images. IEEE International Conference on Acoustics, Speech, and Signal Processing, Proceedings.(ICASSP'03);Vol. 3. IEEE, 2003.

[3] Phung Son Lam, Abdesselam Bouzerdoum and Douglas Chai. Skin segmentation using color and edge information. Seventh International Symposium on Signal Processing and Its Applications, Proceedings, Vol. 1. IEEE, 2003.

[4] Al-Tairi, Zaher Hamid et al. Skin segmentation using YUV and RGB color spaces. Journal of Information Processing Systems, 2014; 10.2 283-299.

[5] Gasparini, Francesca, and Raimondo Schettini. Skin segmentation using multiple thresholding. Internet Imaging. International Society for Optics and Photonics, 2006; VII. Vol., 6061.

[6] Filali Youssef et al. A study of lesion skin segmentation, features selection and classification approaches. International Conference on Intelligent Systems and Computer Vision (ISCV); IEEE, 2018.

[7] Lahoti Sakshi et al. Android based american sign language recognition system with skin segmentation and SVM. 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT); IEEE, 2018.

[8] Reshna S and Jayaraju M. Spotting and recognition of hand gesture for Indian sign language recognition system with skin segmentation and SVM. International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET); IEEE, 2017.

[9] Murugan A, Anu S, Nair H and Sanal Kumar KP.Detection of skin cancer using SVM, random forest and kNN classifiers. Journal of Medical Systems, 2019; 43.8 1-9.

[10] http://cs-chan.com/downloads_skin_dataset.html