A Color Facial Image Segmentation using Bit Plane Slicing and Block Truncation Coding Techniques

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Abstract

Facial image segmentation is vital and complementary in facial compression systems. IT generally represents the first step before using any coding techniques, but mostly utilizes traditional segmentation techniques of grayscale image base due to their simplicity and popularity. This paper introduces a new facial segmented image of the color base that exploits the spectral and spatial image information using differencing coding, and compression techniques of Bit Plane Slicing (BPS) and Block Truncation Coding (BTC), respectively. The tested results show that this technique is fast as it achieved about 0.3619 second on average and efficiently segmented the facial image automatically to nearly quarter the original image size.

Keywords: Facial images, image segmentation, spectral redundancy, block truncation coding and bit plane slicing.

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تجزئة صورة الوجه الملونة باستخدام تقنيات ترميز مستوى البت وتقطيع الكتلة

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الخلاصة

يعد تجزئة صورة الوجه أمرًا حيويًا ومكملًا في أنظمة ضغط الوجه والتي تمثل عمومًا الخطوة الأولى قبل استخدام أي تقنيات الترميز ، ولكنها تستخدم في الغالب تقنيات التجزئة التقليدية لقاعدة الصور الرمادية نظرًا لبساطتها وشعبيتها. يقدم هذا البحث تجزئة جديدة لصورة الوجه الملونة التي تستغل معلومات الصورة الطيفية والمكانية باستخدام تقنيات الترميز والضغط المختلفة لـ PBS و BTC على التوالي. تظهر النتائج المختبرة أن هذه التقنية سريعة وفعالة تقوم بتجزئة صورة الوجه تلقائيًا.

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1. Introduction

Passport-style images, also referred to as facial or personal images, are now widely used in various applications, including personal databases in e-government (E-G) offices, military, universities, and telemedicine patient records[1]. Especially in COVID-19 circumstances (Corona Virus Disease) the need for facial images become urgently required with e-learning platforms, in which these images are used as the identity of an individual in exams and lectures attendances [2]. Additionally, foreign policy and criminal history are two topics that

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come up frequently in this field A passport image of size 448×623 pixels require a storage size of about 818KB in raw format. Depending on the scope of the project and the number of people involved, images in databases takes massive storage space, which directly affects the storage and transmission [1]. The well-known standard joint photographic image format (JPEG) represents the core to compress facial images efficiently, but unfortunately, it still suffers from an inability to consider image regions independently. Namely, using the same principle of redundancy removal of the facial region, non-facial region (i.e., background region). within addition to the inherited problem relating to its block-based nature [2]. Thus, the segmentation process becomes complementary part to enhance the performance.

Segmentation or isolation generally separates the facial (non-background/region of interest (ROI)) part, from the non-facial (background/non-ROI) part. The techniques are broadly classified into edge and object-based, where the former implies abrupt changes in gray level of convolution-based process, while the latter implies continuity in gray level of thresholding, region growing, and split-merge techniques, for more details, see[3][4][5][6][7][8][9][10][11][12]. The choice between them is restricted by application requirements, here the object is based on the facial region utilized.

This paper is concerned with facial segmentation of RGB color images, using compression techniques of bit plane slicing (BPS) and block truncation coding (BTC) The essential part of the proposed system constitutes exploiting the spectral redundancy embedded between RGB color bands with differencing coding along object-based techniques of PBS and BTC that efficient and automatically segments the facial region from the background. More details about the mentioned techniques can found in [13][14][15][16][17][18][19]. The paper is organized into the following sections: Section 2 reviews some related works on facial-based segmentation. Section 3 contains comprehensive clarification of the proposed systems. Finally, the results for the proposed system and the conclusions are presented in sections 4 and 5, respectively.

2. Literature Survey
This section is devoted to reviewing details of facial image segmentation of gray and color-based images, such as:
- Tang, J [20], utilized region growing for a color segmentation algorithm of automatic selection of seed pixels with a combination of the watershed algorithm. The experimental results on some of the non-standard tested color images, where compared to traditional algorithms. this approach has two advantages: First, the region growing step in the traditional seed region growing (SRC) method has a time complexity of O(mlogn), where n is the number of pixels in the original image. Thus, the watershed algorithm generates region as a seed with time complexity of O(mlogm), where m is the number of regions generated by the watershed algorithm of selection seed and regional growth based hue and saturation of the color image. Second, the region contains the amount of information content that is relative to the pixel from the segmentation effect, which is good for region growth and better segmentation results.
- Sulaiman, S., and Isa, N. [21] introduced a new image segmentation clustering algorithm called Adaptive Fuzzy-K-means (AFKM) that mixed between traditional bases of K-means clustering and Fuzzy C-means (FCM) clustering to enhance the segmentation process using fuzziness concept. The tested results achieved better-segmentation results compared to the tradiional techniques for ten tested square images sizes of (512x512) and (256x256) with utilizing both qualitative and three quantitative benchmarks. The first was proposed by Liu and Yang and referred to as F(I), while the second and the third evaluation functions

corresponded to F'(I) and Q(I) respectively. This was adopted by Barsotti et al., where these functions allow the segmentation to be evaluated without labelling the image and without the requirement of user-set parameters. Moreover, these functions correspond more closely to visual judgment. Smaller values of F(I), F'(I), and Q(I), showed better segmentation results criteria to evaluate the efficacy of the suggested approach in additional processing time, the proposed AFKM clustering algorithm acquired a slightly higher processing time as compared to the conventional clustering MKM clustering algorithm. However, the processing time for the FCM and AFKM were almost similar.

- Şener, et al. [22], exploit a Bayesian modelling base to segment facial tissue using 3D MR-CT information. Depending on information fusion from multiple modalities, the Pre-processing starts with MR bias correction, Intensity normalization (MR, CT), and MR-CT image registration. The first stage was scanned with the maxillofacial CT protocol, covering axial slices from Orbita inferior to include the maxillar and mandibular region. The second stage was scanned with the paranasal sinus CT protocol, covering axial slices from the upper frontal sinus to the maxillary and mandibular region. The number of regions of interest (ROIs) selected for evaluation was 16, and each ROI included five consecutive slices of approximately 40×40 pixels (corresponding to a 37mm $\times$ 37mm area). The experiments were applied to different combinations of blurring, partial volume, regularization, and single image or fusion. The computation times were directly affected by various factors, such as the number of classes used, and the size and volume of the image utilized. The results showed that efficient segmentation required at least 10 iterations, for 5 slices of (50 x 50) ROI of a typical fusion instance that needed about 5 seconds. Also, the computing time increases linearly with the size of the image, namely it would need over 20 minutes for 50 slices of a (256x256) image size.

- Nguyen, H., et al. [23], adopted multi-task learning for detecting and segmenting manipulated facial images from videos, using the map manipulated regions for each frame, where the auto-encoder resizes the input image into the fixed square size of 256x256 pixels in order to keep training simple. The dataset utilized was divided into 704 training videos, 150 validation videos, and 150 testing videos with the convolutional neural network with a Y-shaped. The best results were after fine-tuning for Test 4. Classification and segmentation accuracies increased by around 25% and 8%, respectively. The FTRes (Forensics Transfer using residual images as input) and FT (Forensics Transfer using normal images as input) method had better adaptation than the FT.

- Kim, H., et al. [24], introduced a robust facial landmark semantic segmentation (FLSNet) based on dividing images into pixel units. The technique used datasets made up of pairs of facial images and ground truth data as well as a semantic segmentation architecture for in-depth landmark detection. The suggested technique was evaluated through extensive testing using the metrics intersection over union (IoU) and pixel accuracy using 1,789 facial images that made up the entire dataset. It was first split into two training sets, one with 1,432 images and the other with 357. The average of IoU for the FLSNet proposed technique was 0.846.

- LI, Hong-An, et al [25], suggested facial image segmentation based on the Gabor filter, which effectively reduces the false detection rate of facial image segmentation with multiple faces using the AdaBoost algorithm and the Gabor texture analysis algorithm. The technique initially examined for texture using the Gabor algorithm, whereas the background information in skin-like areas of the image is removed by exploiting appropriate thresholds. On the other hand, the AdaBoost algorithm was utilized to identify the detected face regions, followed by

where the total number of faces was 49, the correct face segmentation was 47 and number of missing faces was 2 and the face segmentation accuracy was 95.9.

3. The Proposed System

The suggested system presents a color facial segmentation technique that exploits the spectral statistical redundancy embedded between RGB color bands and the image compression techniques of one band base. In other words, the work aims to utilize the compression techniques efficiently to segment the facial part from non-facial part. Figure (1) shows the steps clearly, also the steps below and algorithms $(1 - 4)$ explain the segmentation process in detail.

Step 1: Load the facial (passport-photo) color input image I of size M×Nx3 then resize it to be of square size NxNx3.

Step 2: Remove the spectral redundancy of color images. This starts by splitting the *I* into its bands (I_R, I_G, I_B), each of size N×N of high spectral redundancy, where I_R, I_G, I_B corresponding to R, G and B image bands. Then select the two highly spectral correlated color bands according to equation (1) using statistical measure of standard deviation base, see algorithm1 which implies the above two steps.

$$2CorBands = \begin{cases} I_R \& I_G & \text{if } StdIR \& StdIG > StdIB \\ I_R \& I_B & \text{if } StdIG \& StdIR > StdIB \\ I_B \& I_G & \text{for } StdIB \& StdIR > StdIG \end{cases} \quad ..(1)$$

Where 2CorBands corresponds to two correlated bands such as I_R & I_G respectively.

Algorithm (1): Pre-Processing steps of Facial Image segmentation
Input:
Reading input color image of size *M×Nx3*
Output:
I_R and I_G *of size NxN* // Two highly correlated bands selected
Begin:
Step1: resize image to be squared image
Step2: splitting color image into 3 bands
Step3: compute the standard deviation for each color band separately
End

Step 3: Apply the difference (subtraction) technique to isolate foreground object (face) from the static background, namely subtract the highly two correlated image bands (I_R, I_G) respectively, see agrithm2:

$$I_{diff} = I_R - I_G \qquad \qquad ... ... (2)$$

Where I_{diff} corresponds to subtract between I_R, I_G.

Algorithm (2): difference (subtraction) technique between two highly selected color bands
Input:
  I_R, I_G // highly two selected colorbands
Output:
    Band (I_{deff}) that result from Subtraction technique between I_R and I_G

Begin:
    Step1: Apply (subtraction) process between highly selected color bands (I_R, I_G)
End

Step 4: Use Bit Plane coding techniques to slice the difference image (I_{diff}) into its layers from 1 to 8 bits, where the least significant values (LSV) of 1 to 4 bits. On the other hand, the most significant values (MSV) of 5 to 8, here layer 6 (bit 6), is adopted to describe facial part effectively.

$$I_{BPS}=I_{diff} \text{ (layer6ofBPS)} \text{…………………... (3)}$$

Where I_{BPS} corresponding to layer 6 of BPS technique.

Step 5: Binarize the selected bits plane slicing IBPS using the traditional BTC technique of mean threshold value (see equation 4), where the resultant image is quantized into two values of binary base to facilitate the segmentation (isolation) process, see algorithm3.

$$FacialBin(x,y) = \begin{cases} 1 & \text{if } IBPS(x,y) > T_{mean} \\ 0 & \text{otherwise} \end{cases} \quad (4.)$$

Algorithm (3): Binarize facial region using bit plane slicing and BTC coding techniques
Input:
Band (I_{diff})
Output:
   Binarize facial region (FacialBin).
Begin:
 Step 1: Apply the bit plane slice technique and   selected the 6th layer.
Step2: //apply BTC resultant from step above.
  a) Partition IBPS into fixed block size of nxn base.
  b) Compute the mean and standard deviation values for each segmented fixed block.
  c) Binarize the IBPS according to equation 4.
End

Step 6: Find the selected region automatically that corresponds to *ROI* using the resultant binary image from the step above FacialBin. The process starts by finding all face (foreground) points with pixel values equal to ones then finding the maximum and minimum values of both directions (*x* and *y* direction) and lastly computing the width and height of the selected important regions according to equations bellow, see algorithm4.

$$Wid_{ROI}=Maximumx\text{-}Minimumx \qquad \text{………. (5)}$$
$$Hgt_{ROI}=Maximumy\text{-}Minimumy \qquad \text{............... (6)}$$

Where Wid_{ROI} and Hgt_{ROI} corresponding to the width (x-axis) and height (y-axis) of ROI.

Algorithm (4): Calculated of ROI and Non-ROI
Input:
Binarize Image region (FacialBin)
Output:
 Region of interest (ROI)
Non Region of interest (Non_ROI)
Begin:
 Step 1: finding the maximum and minimum Values of both directions (*x* and *y* direction)
 Step2: find region of interest (ROI)
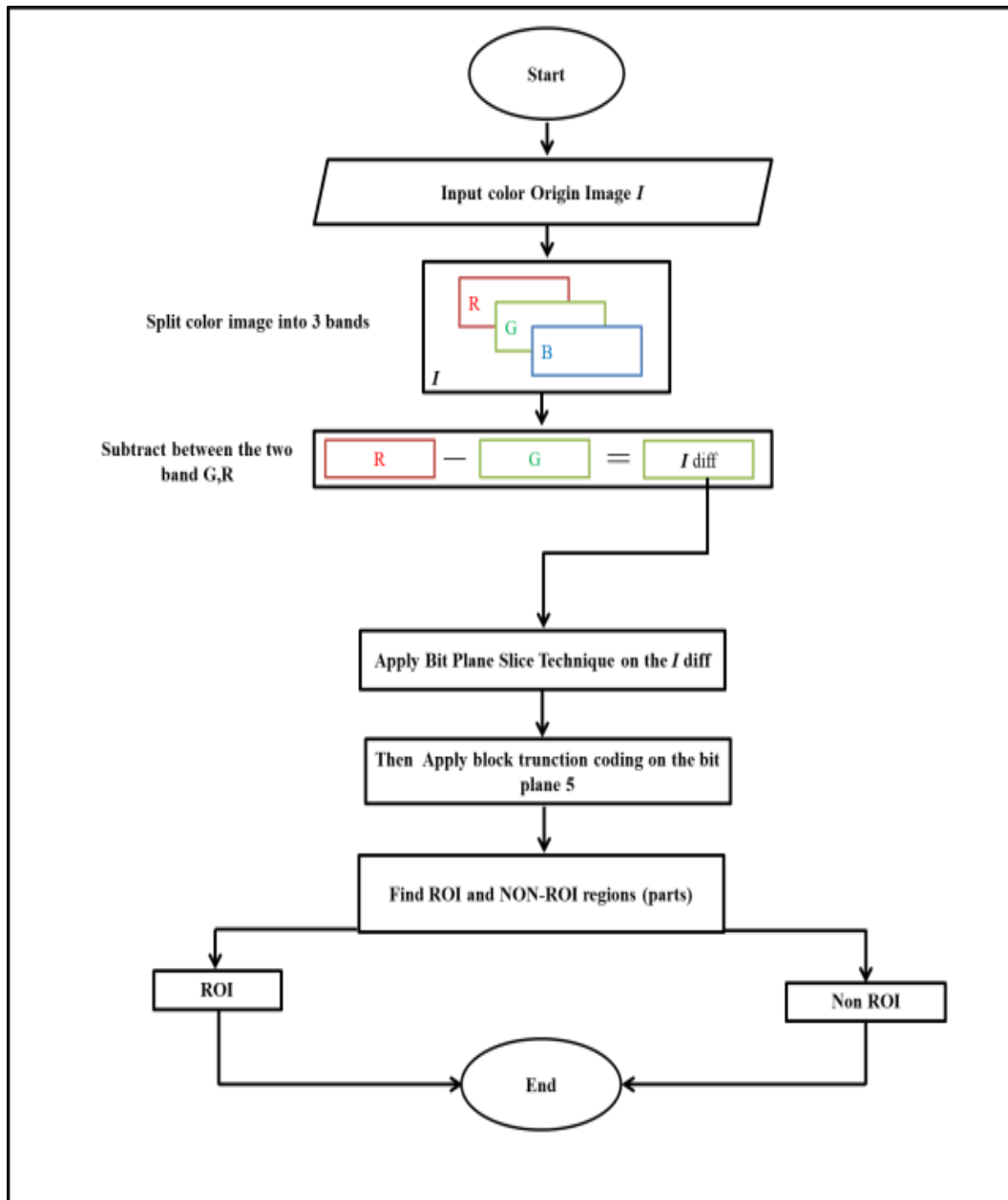 Step 3: find Non region of interest (Non_ROI)
End

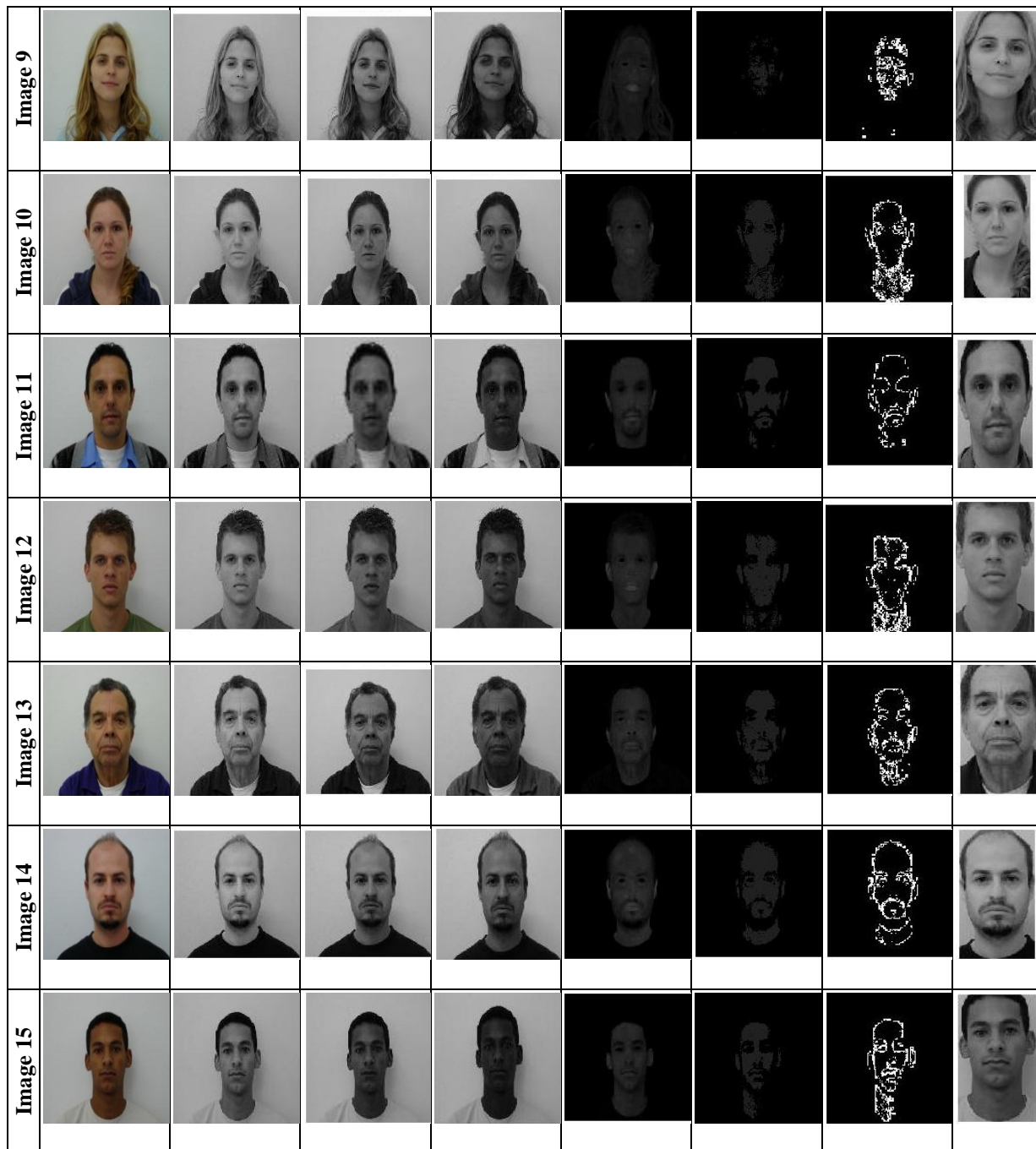**Figure 1:** Flowchart of the proposed segmentation System

4. Results and Discussion

For testing the proposed color facial segmentation system performance, fifteen color standard images were adopted/selected from the facial recognition technology (FERET) dataset, of non-square sizes (640x480 pixels), with a plain background. The input image was first resized to a 256x256 square before being split into three bands, then the subtract technique was used to isolate the facial region from the background followed by BPS, binarized image using BTC, and finally segmented the facial region (ROI) that is shown in Table (1). The images have a variety of lighting, head poses, hair lengths, outfits, sunglasses, and head sizes. Table (2) shows the performance of the proposed system in terms of the size of ROI, the size of bites, and the time required in seconds.

Finally, It is worth noting that the proposed facial segmented system was implemented by using MATLAB application version R201a. This application was installed on a laptop computer with intel(R) Core (TM) i7-5600U CPU @ 2.60GHz   2.60 GHz, 500 GB HDD RAM of 7.88 GB, and Windows 10 Pro Operating system (64 bit).

Table 1: The proposed color facial segmentation system results

	Original image	Red	Green	Blue	Image subtraction	bit-slicing6	BTC	ROI
Image 1								
Image 2								
Image 3								
Image 4								
Image 5								
Image 6								
Image 7								
Image 8								

The results clearly show that the size of the ROI region corresponds to the quarter of the original image size, nearly 25 % of the original image sizes in bytes, which can be seen in Figure (2). With time of segmentation process on average equalling to 0.361 second, see Figure (3).
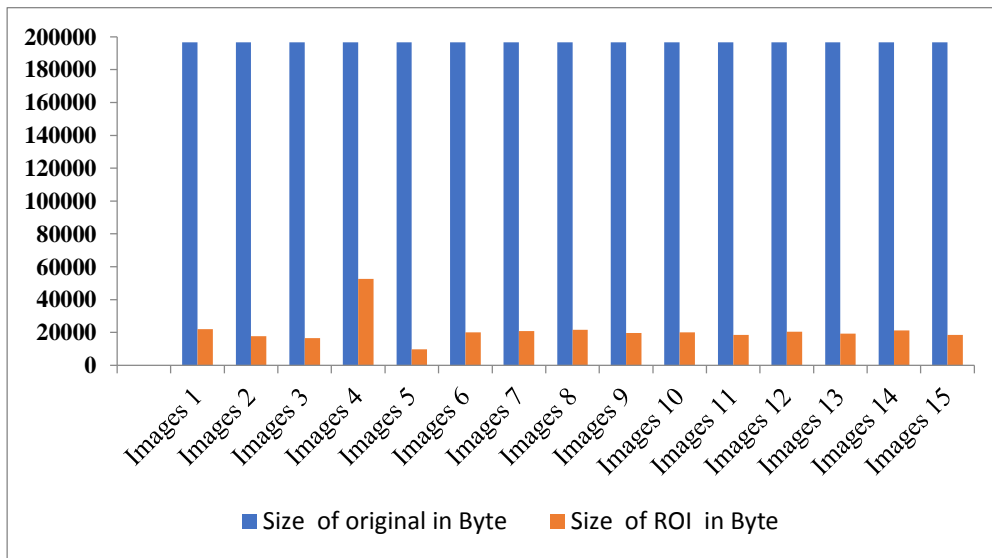
Figure 2: size of the original image and ROI region in bytes for the tested image
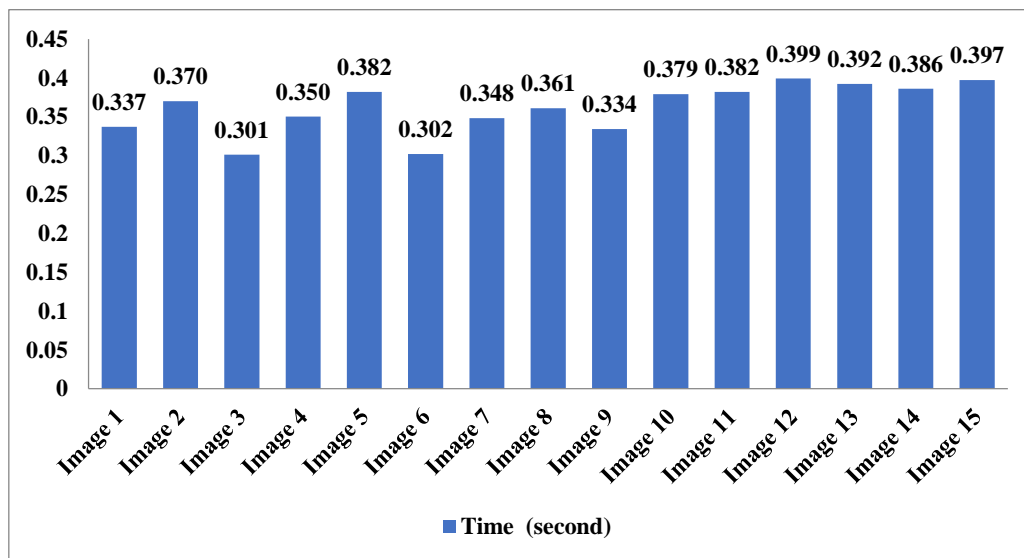

Figure 3: Time of the proposed segmentation process in second for the tested images

5. Conclusions

The proposed technique utilized the spectral color bands along the spatial facial information efficiently, using the mixing between BPS and BTC in which the thresholds were generated automatically. Also, the segmentation process is fast, which makes its promising to use in facial compression system that potentially required 25% ROI image size compared to the non-ROI.

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