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**REVIEW**

# Logistic Regression Based Model for Improving the Accuracy and Time Complexity of ROI's Extraction in Real Time Traffic Signs Recognition System

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ABSTRACT

Designing accurate and time-efficient real-time traffic sign recognition systems is a crucial part of developing the intelligent vehicle which is the main agent in the intelligent transportation system. Traffic sign recognition systems consist of an initial detection phase where images and colors are segmented and fed to the recognition phase. The most challenging process in such systems in terms of time consumption is the detection phase. The trade off in previous studies, which proposed different methods for detecting traffic signs, is between accuracy and computation time. Therefore, this paper presents a novel accurate and time-efficient color segmentation approach based on logistic regression. We used RGB color space as the domain to extract the features of our hypothesis; this has boosted the speed of our approach since no color conversion is needed. Our trained segmentation classifier was tested on 1000 traffic sign images taken in different lighting conditions. The results show that our approach segmented 974 of these images correctly and in a time less than one-fifth of the time needed by any other robust segmentation method.

## 1. Introduction

Road signs are used to regulate traffic, warn drivers, and provide useful information to help make driving safe and convenient [1]. However, driver's ability to recognize them depends on the physical and mental conditions. These conditions can be affected by many factors such as fatigue, and observatory skills [2]. As a result, traffic signs recognition systems were proposed to augment driver's attention so that driving can become safer and more convenient.

The core functionality of traffic signs recognition systems takes place in two phases: the first is traffic sign

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detection (TSD) and the second is the traffic sign recognition (TSR) [3]. In the TSD phase which is the input of the recognition phase, the image is preprocessed, enhanced, and segmented according to the sign properties such as color or shape [4]. About 62% of work done in this field used colors as the basic cue for TSD while the remaining used shape [2,5]. The aim of segmentation process, which turns the captured image into binary image based on a certain thresholding algorithm, is to extract the regions of interest from the whole image [6-9]. The regions of interest are those containing colors that qualify them to contain traffic signs. Due to this role, this phase is of a critical importance because it will narrow the search space that has to be targeted by the system by marking certain areas to be sought after for traffic signs instead of the whole image, so that the work of the next phase will be much efficient. This phase is also challenging since colors information has a considerable sensitivity to lighting conditions [2,10]. If ideal lighting conditions are presented, the task of segmentation will be easy. However, non-ideal illumination conditions are the predominant ones, some of them are the result of excessive daylight, and some are the result of poor lighting either at night or in bad weather conditions. Moreover, regions of interest extraction may be very costly in terms of the computation time depending on the image size [3]. Therefore, in this paper we focus on the TSD phase and we propose an approach for improving the accuracy of detection and reducing its computational time.

Previous studies proposed different fundamental approaches to deal with TSD accuracy and time complexity. For example, to overcome the issue of sensitivity, most of the previous work followed the approach of color space conversion, where the captured images which are originally represented in the RGB color space are transformed into another space like HSV(hue, saturation, value)/HSL(hue, saturation, lightness) or IHLS(Improved Hue Luminance Saturation) [1,2,4,6,9]. These spaces are used because chromatic information can be easily separated from the lighting information making this approach more suitable for detecting a specified color in almost all light conditions. This approach produced relatively accurate results but in a high computational time.

To avoid high computational complexity, some research used RGB color space with minimal computations [7,11]. However, this approach suffers from low accuracy. Another avoidance mechanism depended on statistical distribution findings which conclude that most traffic signs appear in the middle of the image and a few in the top with relatively large scales [12]. Such assumption reduces the robustness of the system and limits the detection of some real traffic signs which are not subject to the supposed distribution due to some poses of the vehicle like turning around or driving downhill. Another limitation is that the proposed system requires the vanishing horizon to be roughly in the middle of the captured image, which is not always the case [12]. Another approach was proposed to identify color space by using Maximally Stable Extremal Regions (MSERs) [3,13]. This approach resulted in a very precise detection. However, it is not sufficient alone to produce results that could be used as inputs to the recognition phase because it obtains traffic signs with a large number of backgrounds [3]. To enhance MSERs work, some research made refinement for the produced ROI's in the recognition phase like what was proposed in [3]. In [13], MSERs was used along with a complementary shape-based extractors which would eventually consume a considerable amount of time.

In this paper we propose a novel TSD model that has high performance and simultaneously balances between the accuracy and computational complexity. We use logistic regression, a simple but powerful machine learning technique for the segmentation. Logistic regression is the appropriate when the dependent variable is binary. It is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables [14]. To evaluate our model, we used a total of 1000 images of local traffic signs and other images downloaded from 'Belgian Traffic Sign Dataset' [10]. Our model outperformed other related methods in terms of accuracy and computation time.

## 2. Related Work

Previous studies can be divided into two main groups depending on the color spaces used in segmenting the images. The first group contains studies that adopted the approach of color space conversion before thresholding, and the second contains those who have used the RGB color space as the domain for processing.

### 2.1 Converting RGB Image into Another Color Space

This approach is the most popular since its results are more robust and it covers wider cases under different lighting conditions. The two dominant color spaces used by the advocates of this approach are HSI(hue, saturation, intensity) [1,15,16] and HSV [4,6,9]. These color models are used extensively because they do a separation between the colorfulness and the lightness of the image so that there is independence between the chromatic and achromatic components. This makes extracting a good threshold an easier task. However, converting from the RGB to those color


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spaces consumes long time since it involves a non-linear transformation [17].

### 2.2 Using RGB for Segmentation

The aim of working directly with RGB is to design much faster segmentation algorithms. The idea of using the RGB in segmentation is based on an observation that the differences between the color component of the sign and the other two colors components remains relatively high and could easily be used with an appropriate (not too sensitive) threshold for segmentation [18]. Hence, a simple segmentation algorithm can be implemented using the three differences: ΔRG, ΔRB and ΔGB which need not be selected very precisely [11].

However, another research based on this algorithm have concluded that using constant ΔGR, ΔGB and ΔRB for different non-ideal illumination conditions throughout the whole day and night is not appropriate. They developed the idea of using different adaptive color threshold values for different non-ideal illumination conditions at different times in the day and night. They adapted the threshold values based on the intensity or brightness of the time. The intensity value that was used as a threshold, it was calculated using the following formula [5]:

$$I = \frac{R + G + B}{3} \quad (1)$$

However, even when using adaptive threshold, this algorithm has a problem that there are no set of threshold values that yield a very good segmentation. The range of the threshold values may be narrow so that some signs are going to be lost, or wide so that many parts of the image will be segmented as regions of interest. We tested this approach on a local traffic sign image as shown in figure 1 which shows an example of adaptive wide threshold. The figure shows that colors that have dominant red component for example orange and brown will be segmented as if they are red. That is because the differences between the red component and the other two components relative to the average of the three components are similar to what is found in some shades of the red color.

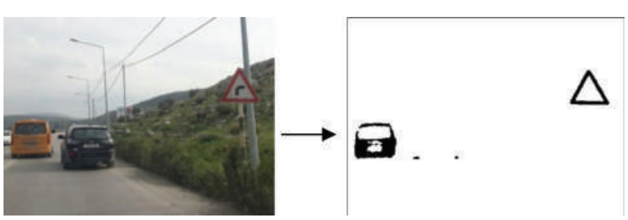

**Figure 1.** Wide range segmentation based on adaptive thresholding in which other objects with colors close to red are segmented as a red traffic sign

## 3. Logistic Regression based TSD Model

### 3.1 Theoretical Background

We investigated the road signs color segmentation problem as a machine learning problem. We used logistic regression classifier as a segmentation algorithm. Logistic regression is a classification algorithm used to derive a hypothesis $h_0(x)$ given training data represented as a features vector $x=\{x_1,x_2,x_3 ..., x_n\}$ and a target function $(\theta^T x)$, this is done by estimating a set of values for weights $\theta^T$ that achieves the best mapping between input and output values given in the training data. The derived hypothesis categorizes new observations under a discrete set of classes. It uses sigmoid function to map real values into probabilities between 0 and 1. The following set of equations describes how the sigmoid is used to do this mapping:

$$h_0(x) = S(\theta^T x) \quad (2)$$

$$Z = \theta^T x \quad (3)$$

$$S(z) = \frac{1}{1 + e^{-z}} \quad (4)$$

Where θ is the values of the model's weights and the bias, $x$ is the features of training data used in the target function, and  is the sigmoid function. The estimation of θ values is done by an ongoing minimization of the cost function (the deviation of the hypothesis prediction from the actual output) during the learning phase. The cost function is given by:

$$Cost\,(h_0(x), y) = -y\,log(h_0(x)) - (1-y)log(1-h_0(x)) \quad (5)$$

where y is the actual output value.

### 3.2 The Proposed Model

We derive our approach based on the results proposed by Benalla et. al.[11] that the differences ΔRG, ΔRB and ΔGB are indicators of the sign color. We also borrowed Sajjad et. al.[7] approach of searching for efficient adaptive threshold. However, instead of dealing with these differences as mutual exclusive conditions to decide the threshold, we have modeled them together as variables/features in a function where each of them contributes simultaneously to the decision-making process. This way the relative value of each difference to the other two decides the threshold, as such we have avoided the aforementioned issue shown in figure 1 of getting either a narrow or a wide threshold. Another feature we added to our function is the value of the desired color component of a certain sign (blue or red in our case). This is because we have noticed that the relations between the three differences are not adequate to judge the color in all cases, especially when the difference between two of them are approaching to zeros. Measuring their values relatively to the value of the desired color



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was the solution to avoid failing in such cases. The values of these four features contributions in determining the threshold are the weights associated with these features. We have used logistic regression technique to estimate the best values of these weights. Figure 2 is simple a description of the model.

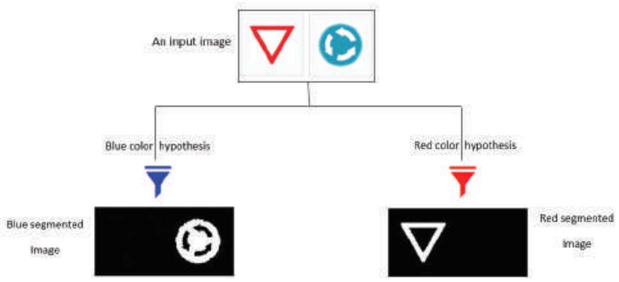


**Figure 2.** Abstract representation of segmentation process

As shown in the figure 2, an image goes under two segmentation thresholds that are executed in parallel and produce two binary images. Each binary image contains regions having pixels of needed color as ones and other pixels as zeros.

The Red threshold hypothesis is given by:

$$h_\theta(x) = S(\theta_0 + \theta_1 R + \theta_2 \Delta RG + \theta_3 \Delta RB + \theta_4 |\Delta GB|) \quad (6)$$

and Blue threshold hypothesis is given by:

$$h_\theta(x) = S(\theta_0 + \theta_1 B + \theta_3 \Delta RB + \theta_4 \Delta GB + \theta_2 |\Delta RG|) \quad (7)$$

where $S$ is the sigmoid function, R is the red component of the pixel in RGB model in the range [0–255], G is the green component of the pixel [0–255], and B is the blue component of the pixel [0–255]. when thresholding for a color, the difference between the other two colors is considered as a magnitude, because its sign is not important, what is important is the ratios between its magnitude and the values of other features.

We classify the pixel as red/blue if the value of the hypothesis (the probability that this pixel is red/blue) is equal to or greater than 0.5 (see figure 3); in other words, if the value of the target function is greater than or equal to zero the pixel is classified as red/blue. Hence our classifier can be represented by:

$$P = \begin{cases} Red, \theta_0 + \theta_1 R + \theta_2 \Delta RG + \theta_3 \Delta RB + \theta_4 |\Delta GB| \geq 0 \\ Blue, \theta_0 + \theta_1 B + \theta_3 \Delta RB + \theta_4 \Delta GB + \theta_2 |\Delta RG| \geq 0 \end{cases} \quad (8)$$

where $P$ is the pixels of the image.

The following is the pseudo code of the core function of our model, which receives a road image '*Image*' and the segmentation color '*Desired_Color*' as inputs and returns a segmented/binary image '*Image_2*' as an output:

***INPUT***
*1: desired_color // the color of the segmentation, it takes the value of **red** or **blue***
*2: image // the image taken from real time capturing unit I.e. a camera*
***BEGIN***
*3: image = ConvertToSinglePrecision(Image)*
***if*** *desired_color = red* ***then***
*c1 = image(*,*,1) //Red color component of Image*
*c2 = image(*,*,2) //Green color component of Image*
*c3 = image(*,*,3) //Blue color component of Image*
***else if*** *Desired_Color = blue* ***then***
  *c1 = image(*,*,3) //Blue color component of Image*
  *c2 = image(*,*,2) //Green color component of Image*
  *c3 = image(*,*,1) //Red color component of Image*
***end if***
*diff_1 = c1 – c2*
*diff_2 = c1 – c3*
*diff_3 = |c2 – c3|*
*image_2 = + c1 + Diff_1 + Diff_2 + Diff_2 + Diff_3 ≥ 0*
***return*** *Image_2*
***END***

### 3.3 Training and Testing the Model

The data set used for training the model includes 300 local images captured in different lighting conditions in Palestine. The images contain signs from different types, for example, signs giving warnings, signs giving orders and information signs as shown in figure 3. For testing the proposed model, we used another data set includes 1000 traffic sign images obtained online from 'Belgian Traffic Sign Dataset' found at http://btsd.ethz.ch/shareddata/.


**Figure 3.** examples of Traffic signs used in Palestine

To train our model, we have created a set of segmented images; in the training data each training entity consists of our four feature values and the corresponding output value at the pixel level. We used the 'Minimize a continuous differentiable multivariate function' proposed by Carl Edward Rasmussen in 2002 to derive the weights value.

To evaluate our model, we compared it with other related studies that have robust results [1-4,6,9,15-17]. We implemented the core functionality of their models which entails color spaces conversion using the same programming language we used in our implementation and under the same hardware specs; and the same dataset.

Our derived hypothesis is implemented using Matlab and we have thoroughly assessed the performance of the model using Matlab profiler. The model was implemented on a CPU with specifications: *Intel(R) Core(TM) i5-6200U CPU @ 2.30GHz, 3 MB SmartCache, 2 Cores and 4 Threads.* We used vectorized instructions in all image-pixels manipulation operations to optimize the performance. A detailed discussion of the performance and accuracy is discussed in the following section.

## 4. Results and Discussion

### 4.1 Accuracy

The proposed model shows dependable results as of the 1000 test images 974 were segmented correctly. This accuracy of about 97.4% outperforms that of the previous models as shown in Table 1. We define the accuracy as the percentage of correct detections.

**Table 1.** Accuracy comparison of different models used for TSD

| Model | Accuracy % |
|---|---|
| The proposed model | 97.40 |
| [18] | 94.85 |
| [3] | 93.54 |
| [6] | 92.98 |
| [12] | 94.41 |
| [9] | 89.32 |

The results shown in the figure 4 depict samples of model accuracy under different lighting conditions. The segmented images allow perfect determination of ROI's which form the domain of search for the recognition phase.

The images that were not segmented correctly are only those signs whose colors are extremely deteriorated.

### 4.2 Computational Time:

The proposed model also reduces the time required for

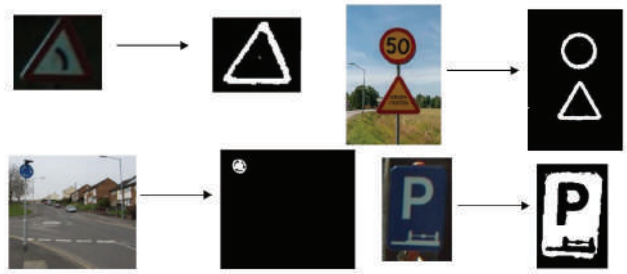


**Figure 4.** Our model test results samples

TSD. Previous studies that provided accurate results have based their work on converting from RGB color space to other color spaces. However, they did not provide a detailed performance measurement of their algorithms complexity. So, to give an indication of the performance comparison between our work and theirs, we compare the time taken by our model with that needed to merely converting an image from RGB to the required color spaces. Table 2 shows the time needed to detect a sign with different image sizes. For each image size, we took the average time needed for RGB To HSV in the studies [4,6,9] and for RGB To HIS in the studies [1,15,16].

**Table 2.** Computational time comparison for different models used for TSD

| Image Size in pixels | Time in seconds | | |
|---|---|---|---|
| | Proposed model | RGB To HSV | RGB To HSI |
| 87 * 174 | 0.000195 | 0.002001 | 0.002042 |
| 800 * 556 | 0.008231 | 0.071822 | 0.035139 |
| 768 * 1024 | 0.017002 | 0.116413 | 0.071002 |
| 1536 * 2048 | 0.057206 | 0.815914 | 0.319685 |
| 2448 * 3264 | 0.141652 | 1.278549 | 0.572381 |

As shown in table 2, our model outperforms other related models with different image resolutions. As can be inferred from the table, our model is faster than other models that have a competing accuracy. And this is a crucial benefit, because computation time is a key component in every real time application, especially in intelligent transportation system where parts of a second can make a great difference. Table 2 shows that the time needed for converting from the RGB to other color spaces, before doing any thresholding, is more than five times of the time needed to do a total segmentation of the image in the RGB color model using an efficient algorithm.

## 5. Conclusion

This paper proposes a novel model of addressing a challenging part of traffic sign recognition systems that is traffic sign detection in which the sign image is segmented and the ROI's are determined. The proposed model uses logistic regression as an image thresholding algorithm. It



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operates on the RGB color model and does not use any color space conversions. The proposed model provides a high level of accuracy of about 97.4%, with very time-efficient results. The application of our approach will help to design higher performance complete traffic signs recognition systems. Our future work will focus on developing the second phase which is a model for traffic sign recognition that utilizes the proposed TSD model.

**References**

[ 1 ] C.-Y. Fang, S.-W. Chen, and C.-S. Fuh, "Road-Sign Detection and Tracking," IEEE Trans. Veh. Technol., 2003, 52(5).

[ 2 ] H. Fleyeh, "Color detection and segmentation for road and traffic signs," in IEEE Conference on Cybernetics and Intelligent Systems, 2004, 2, 809–814.

[ 3 ] H. Luo, Y. Yang, B. Tong, F. Wu, and B. Fan, "Traffic Sign Recognition Using a Multi-Task Convolutional Neural Network," IEEE Trans. Intell. Transp. Syst., 2018, 19(4), 1100–1111.

[ 4 ] H. Fleyeh, "Road and Traffic Sign Color Detection and Segmentation - A Fuzzy Approach," in Conference on Machine VIsion Applications, 2005, 3–27.

[ 5 ] E. De Micheli, R. Prevete, G. Piccioli, and M. Campani, "Color cues for traffic scene analysis," in Proceedings of the Intelligent Vehicles' 95. Symposium, 466–471.

[ 6 ] N. Beg, M. Agrawal, R. Pasari, A. Singh, and K. H. Wanjale, "Traffic Sign Recognition System," Int. J. Res. Advent Technol., 2016.

[ 7 ] M. S. Hossain, M. M. Hasan, M. Ameer Ali, M. H. Kabir, and a B. M. Shawkat Ali, "Automatic detection and recognition of traffic signs," 2010 IEEE Conf. Robot. Autom. Mechatronics, 2010, 286–291.

[ 8 ] A. Broggi, P. Cerri, P. Medici, P. P. Porta, and G. Ghisio, "Real Time Road Signs Recognition," 2007 IEEE Intell. Veh. Symp., no. section III[1] A. Broggi, P. Cerri, P. Medici, P. P. Porta, and G. Ghisio, "Real Time Road Signs Recognition," 2007 IEEE Intell. Veh. Symp., section III, 2007, 981–986,981–986.

[ 9 ] A. Shustanov and P. Yakimov, "CNN Design for Real-Time Traffic Sign Recognition," Procedia Eng., 2017, 201, 718–725.

[10] R. Timofte, K. Zimmermann, and L. Van Gool, "Multi-view traffic sign detection, recognition, and 3D localisation," Mach. Vis. Appl.,2014, 25(3), 633–647.

[11] M. Benallal and J. Meunier, "Real-time color segmentation of road signs," in CCECE 2003 - Canadian Conference on Electrical and Computer Engineering. Toward a Caring and Humane Technology (Cat. No.03CH37436), 2003, 3, 1823–1826.

[12] Y. Yuan, Z. Xiong, and Q. Wang, "An Incremental Framework for Video-Based Traffic Sign Detection, Tracking, and Recognition," IEEE Trans. Intell. Transp. Syst., 2017,18(7), 1918–1929.

[13] S. Salti, A. Petrelli, F. Tombari, N. Fioraio, and L. Di Stefano, "A traffic sign detection pipeline based on interest region extraction," Proc. Int. Jt. Conf. Neural Networks, 2013.

[14] S. Caballé and J. Conesa, Software Data Engineering for Network eLearning Environments, 2018, 11. Cham: Springer International Publishing.

[15] P. Arnoul, M. Viala, J. P. Guerin, and M. Mergy, "Traffic signs localisation for highways inventory from a video camera on board a moving collection van," in Proceedings of Conference on Intelligent Vehicles, pp. 141–146.

[16] L. Priese, R. Lakmann, and V. Rehrmann, "Ideogram identification in a realtime traffic sign recognition system," in Proceedings of the Intelligent Vehicles '95. Symposium, pp. 310–314.

[17] A. Mavrinac, J. Wu, X. Chen, and K. Tepe, "Competitive learning techniques for color image segmentation," Proc. Mach. Learn. Comput. Vis., 2007, 88, (590), 33–37.

[18] S. B. Wali, M. A. Hannan, S. Abdullah, A. Hussain, and S. A. Samad, "Shape Matching and Color Segmentation Based Traffic Sign Detection System," Prz. Elektrotechniczny, 2015,91(1), 36–40.