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Augmented Reality Labels for Security Signs based on Color Segmentation with PSO for Assisting Colorblind People

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Abstract. There are people who cannot perceive the entire spectrum of colors, this condition is called Colorblindness, which affects around 10% of worldwide population. Colorblindness distresses several situations in daily life and security is one of those, since several norms around the world that regulate security signs including the norm NOM-026-STPS-1998 use color for classifying them. However augmented reality is an emerging approach for assisting people in industrial environments, especially with the so called 4th industrial revolution or industry 4.0. Augmented reality uses complex techniques of computer vision, that recently have been replaced by artificial intelligence algorithms, in this paper is proposed an assistant of augmented reality that labels security signs identified with color segmentation achieved by classifying colors with proposed linear equations depending directly from RGB space, those equations are optimized with a PSO algorithm, and with that color information signs are recognized and labeled for been retransmitted to the user.

Keywords: PSO, Color Classification, Augmented Reality, Security Signs, Colorblindness.

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1 Introduction

Vision is the most important sense of humans because they used it for identifying several objects in their surroundings including food and dangers, this sense is involved in reading, writing, driving, learning, working among other several activities [1].

Human beings get vision information through two types of cells in its eyes; rod cells that are used for perceiving wave length of light i.e. luminosity and cone cells that are sensible to wave frequency of light i.e. colors. Average persons have three types of cones for perceiving red, green and blue tones [2].

Color sense is perceived in the brain with neurons that are activated when light strikes the frequency of a cone and the entire colors are sensed as a combination of sensorial information coming from those cones and interacting with the vision neurons [3, 4].

There are people who cannot distinguish the average human perceived spectrum of colors, this condition is called colorblindness, described initially by John Dalton in 1793 who was colorblind. Colorblindness is considered a mild disability, since people who suffers from this condition have difficulties for living and interacting with a world designed for people with an average perception of colors, called trichromats. These problems involve identification of objects, interpretation of signs and educational activities with colored material, among others [2, 5].

Colorblind people confront several situations in his life like trichromats but its condition commonly affects the clothes that they wear, the food that they cook, the sports that they play and even the career that they choose, the responsibilities in their jobs, the

job positions allowed for them because in industrial environments security is sometimes supported by colored signs that they cannot interpret and this could cause accidents for people with its condition [2, 4, 6].

Colorblindness is present in about 10% of the world population. Most people that suffers colorblindness have mild severity and the most critical variants of this condition have lower occurrence. The Table 1 shows the percentages of worldwide prevalence of the different variants of colorblindness, their names and colorblindness related [2, 5].

Table 1 Colorblindness variants its blindness associated and percentage of occurrence [2].









Colorblindness quantity of cones variant	Color cone sub-variant	Blindness associated	Occurrence M/F	
Monochromacy	Achromatopsia	All colors	0.00003%	
Dichromacy	Deuteranopia	Green	1.27 %	0.01%
	Protanopia	Red	1.01%	0.02%
	Tritanopia	Blue	0.0001%	
Anomalous Trichromacy	Deuteranomaly	Green	4.63%	0.36%
	Protanomaly	Red	1.08%	0.03%
	Tritanomaly	Blue	0.0002%	

People who suffer of colorblindness are also affected by official regulations of security in industrial environments and institutions because they use colors for assist people whit signs, paths, floor boundaries, special uniforms for assisting workers among other regulations related to maintain people safe while there are moving around. An example of this regulations is the Mexican norm NOM-026-STPS-1998 which attend to colors, security signs, sanitation, and risks identification [6].

As an alternative this norm tries to identify using geometrical figures instead of colors for people who have difficulties identifying them, however, not always is possible to mark with these forms some materials, paths or dangerous machines that are painted with specific colors to warn people in their surroundings. Moreover, during the training stage or the learning curve when people is getting custom to the place where they work those who suffer of colorblindness would have greater difficulties than trichromats specially distinguishing dangerous areas marked with colors.

The norm NOM-026-STPS-1998 distinguish situations with signs and colors like is described in the Table 2.

Table 2 Geometrical forms, colors and examples of sign regulations in the NOM-026-STPS-1998 [6].

Meaning	Geometrical Form	Color Associated	Examples
Forbidden		Red with black	
Required		Blue with white	
Warning		Yellow with black	
Information		Green with white	

An alternative to identify the security signs in industries and institutions regulated with norms like the NOM-026-STPS-1998 is the use of Augmented Reality (AR) for assisting colorblind people.

AR it is an emerging approach in industrial environments, that mixes the projection of computer graphics and the reality perceived by the users in their environs, the information required for implementing AR is commonly acquired by using cameras with color segmentation, object recognition among other image processing techniques that have been widely studied. AR commonly highlight paths, regions, or provide informative annotations in other applications for maintaining security [7].

Industrial environments are well accepting AR applications in several areas because together with internet possibilities and Artificial Intelligence (AI) are offering several advantages that include interoperability, virtualization, decentralization, real time capability, service orientation and modularity, all of them important in the so called 4th industrial revolution or Industry 4.0 [8].

In that sense an application for assisting colorblind people mixing together AR and AI techniques it is an approach that concerns to Industry 4.0 since AR applications are related with 4th industrial revolution [8].

AI is recently improving results over several classical techniques by using deep learning which has obtained better performance that those registered with models obtained by humans, an example of these are the representations previously used in classical Computer Vision (CV). CV is an interdisciplinary subject that apply mathematics, statistics, physics, biology and learning theory for obtaining information of images, making CV an alternative to solve several situations in areas that include robotics, industrial inspection, quality, control, medical diagnosis, remote sensing, image retrieval, object recognition, surveillance, assistance among other applications [9].

However deep learning demands great computational power for training and implementing its representations, for example in Convolutional Neural Networks (CNN) are required several numerical data and mathematical operations for its functioning but sometimes computational power is not necessary if the CV techniques have good performance, situation in which CV should be applied [10].

Moreover, there are some works where AI is not correctly applied since CV transformations are used for preparing input data for being used with AI techniques, even when they could outperform its function if they are well implemented by itself without any adaptation. Some of the CV models with good performance that remain in use today are the color representations and they are even used for interacting with AI techniques that could perform the color segmentation task without require those CV models that only demands computational power and increases processing time [11].

Color models that are commonly applied for interacting with AI techniques for color classification include the color representation in digital images, those representations include RGB, HSV, YCbCr, YIQ, YUV, CIElab, among others. But the color models that are natively obtained from digital cameras are RGB, YCbCr and YUV. Using these native representations suppress the time required for transforming basic representations to models that simplify color segmentation, which can be omitted if the AI technique is connected directly to the native color representations, like is described in [11, 12].

Most of the works that are using AI techniques for color classification are implemented with Artificial Neural Networks (ANN), Genetic Algorithms (GA) and PSO algorithms, several of them are mixed with CV models that are not required, in the table below are described the works founded that perform color classification using AI, several of this works where previously analyzed in table 3 complementing the works founded in [12].

Table 3 Analysis of works using color segmentation with AI techniques.

Work Title	CV used	AI used	Description	Reference and year
Comparative of Effectiveness When Classifying Colors Using RGB Image Representation with PSO with Time Decreasing Inertial Coefficient and GA Algorithms as Classifiers	RGB	PSO and GA	The classification of color is successfully applied without transform native RGB representation and is tested using for optimizing GA and PSO, with better results in PSO.	2018 [12]
Case study in effects of color spaces for mineral identification.	RGB, HSV, CIElab	ANN	Three transformations are used for comparing results in mineral identification and despite of HSV and CIElab are color segmentation representations RGB has the best performance.	2016 [13]
Continuous real-time monitoring and neural network modeling of apple slices color changes during hot air drying	CIElab	ANN	Transform to CIElab representation for classifying drying levels in apples based on color classification using ANN.	2015 [14]
Implementation of neural network for color properties of polycarbonates	CIElab	ANN	Transform to CIElab representation for classifying drying levels in apples based on color classification.	2014 [15]
Color space selection for human skin detection using color-texture features and neural networks	YCbCr, YIQ, YDbDr and CIElab	ANN	Human skin detection is made by transforming to different color spaces and they are used as training inputs in an ANN.	2014 [16]
Modelling of color perception of different eye colors using artificial neural networks	CIElab	ANN	CIElab representation is used for training an ANN that evaluates the relation between color preference and color eye classification.	2013 [17]
A genetic algorithm for color image segmentation	Graphs segmentation	GA	Uses the technique of graph segmentation of CV tuned with GA	2013 [18]
Performance measure of human skin region detection based on hybrid particle swarm optimization	CIElab	PSO	RGB space is transformed to CIElab for tuning the model selected with PSO algorithm, for skin detection.	2012 [19]
A PSO tuning approach for lip detection on color images	CElab	PSO	RGB space is transformed to CIElab for tuning the model selected with PSO algorithm for color detection.	2008 [20]

In this paper is presented an alternative where pure AI is used without require CV techniques for determining the color perceived. The technique selected for the classification task apply the equations described in [11] adding two new equations for classification of black and white colors, this equations are optimized with PSO since has exhibit better results than GA in [12] and does not require high computational power for being implemented, after that classifier is trained and then is used for developing an AR assistance of colorblind people interacting with security signs, by labeling the original perceived images mixing reality and graphical contend for allowing people to distinguish the security sign class even if they does not have the regulatory form in the NOM-026-STPS-1998.

2 Background

In this section there are described all the required concepts and reference framework related to the proposed methodology for classifying and labeling security signs.

2.1 Image Processing

Digital images are captured from digital cameras using sensorial units that transform luminosity to voltage signs, those units have frequency filters adapted for perceiving red, green and blue light just like the average human eyes do. These values generate a representation of colors that can be charted in a three-dimensional space, like is shown in Figure 1 [11, 12].

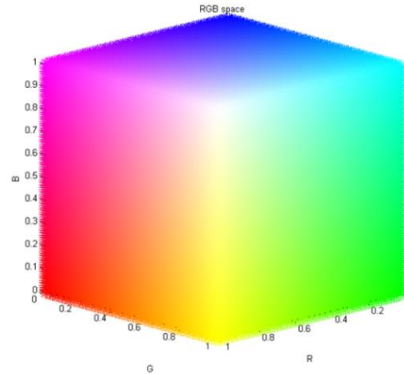


Fig. 1 Space RGB for color representations in digital images [11].

The RGB space require no linear and complex functions to separate colors for classification in \mathbf{R}^3 , however if it is transformed into three \mathbf{R}^2 spaces with projections like is described in [11], then is possible to separate the colors using three linear functions per color depending from the RGB space, those linear equations are described in equations (1) ,(2) and (3).

$$r \leq \alpha_1 \cdot g + \alpha_2 \tag{1}$$

$$g \leq \alpha_3 \cdot b + \alpha_4 \tag{2}$$

$$\alpha_5 \leq r \leq \alpha_6 \tag{3}$$

where r , g and b are the three basic color values per pixel associated to the RGB representation, and α_n with $n = 1, \dots, 6$ are the 6 parameters required for classifying the colors red, orange, yellow, green, blue and violet as is used in [12].

2.2 Particle Swarm Optimization

PSO is a Swarm Intelligence (SI) technique originally proposed in 1995 by Eberhart and Kennedy, that optimizes numerical parameters like those α_n required for tuning the equations for color classification. The PSO algorithm is inspired in bird food flocking, and is algorithm starts by randomly initializing the \mathbf{X}_i position of i particles around the search space, the position of those particles is updated with its velocity \mathbf{V}_i which is initially set to zero for all particles in its D search space dimensions. The main operators in this optimizing algorithm are its personal and social components depending from the best position known for each particle denoted by \mathbf{P}_i in the personal component and the best position know by the entire swarm \mathbf{P}_g required in the social component [12].

To know which the best positions are, cost function $F(\mathbf{X}_i)$ must be evaluated and in a minimizing problem best position is found when $F(\mathbf{X}_i) = 0$.

After that \mathbf{X}_i is used for determining \mathbf{P}_i and \mathbf{P}_G using $F(\mathbf{X}_i)$, then the velocity of each particle is calculated for the actual iteration t depending from previous iteration $t-1$ with equation (4)

$$\mathbf{V}_i(t) = w \cdot \mathbf{V}_i(t-1) + c_1 \cdot r_1 [\mathbf{P}_i - \mathbf{X}_i(t-1)] + c_2 \cdot r_2 [\mathbf{P}_G - \mathbf{X}_i(t-1)] \quad (4)$$

where the parameter w is the inertial coefficient included in a variation of original PSO added 1998 by Eberhart that increase exploration of search space in the initial iterations of the algorithm, the parameters c_1 and c_2 are the personal and social coefficients respectively and are commonly set it to the value of 2.

After that \mathbf{V}_i is determined then position \mathbf{X}_i of the actual iteration is updated using equation (5) depending from the previous iteration.

$$\mathbf{X}_i(t) = \mathbf{X}_i(t-1) + \mathbf{V}_i(t) \quad (5)$$

Finally the new \mathbf{X}_i is used for determining again \mathbf{P}_i and \mathbf{P}_G using $F(\mathbf{X}_i)$. The loop is repeating until a desired cost value is obtained or a maximum number of t iterations.

The algorithm 1 describes general implementation of PSO according to 1998 proposed variation by Eberhart.

```

INPUT  $c_1, c_2, w$ 
Initialize  $\mathbf{X}_i$  and  $\mathbf{V}_i$ ;
 $\mathbf{P}_i = \mathbf{X}_i$ ;
FOR 1 to  $i$ 
    IF  $F(\mathbf{X}_i) \leq F(\mathbf{P}_G)$  THEN
         $\mathbf{P}_G = \mathbf{X}_i$ ;
    ENDIF
ENDFOR

WHILE  $t < \max\_t$ 
Update Velocity  $\mathbf{V}_i$  with equation (4);
Update Position  $\mathbf{X}_i$  with equation (5);
Evaluate value with cost function  $F(\mathbf{X}_i)$ ;
    FOR 1 to  $i$ 
        IF  $F(\mathbf{X}_i) \leq F(\mathbf{P}_i)$  THEN
             $\mathbf{P}_i = \mathbf{X}_i$ ;
            IF  $F(\mathbf{X}_i) \leq F(\mathbf{P}_G)$  THEN
                 $\mathbf{P}_G = \mathbf{X}_i$ ;
            ENDIF
        ENDIF
    ENDFOR
ENDWHILE
RETURN  $\mathbf{P}_G, F(\mathbf{P}_G)$ ;

```

Algorithm 1 General description of implementation of PSO algorithm [12].

3 Methodology

In this section is described the general followed methodology for determining color model for color recognition, its adaptation for classifying security signs and the implementation for the AR labeling.

3.1 Determining Color Model

The color model is based on the equations (1), (2) and (3) described in section 2, for recognizing blue, brown, green, orange, red, violet and yellow colors, but in the work described in [12] used as reference for this paper there are not mentioned the models for white and black colors, which are required in this work since security signs also have part of them with this colors. In that sense here are proposed these two models that was reviewed for obtained better results.

Since both white and black colors do not depend from its tone value but from luminosity it is possible to simplify the detection of them by setting ranges for the values red, green, and blue. This allows to expect high ranges for white colors and low ranges for black colors.

In general, this idea can be supported since both black and white are the same colors only varying by a scalar γ luminosity value that equally affects R, G and B values, like is shown in equation (6).

$$(r, g, b) \cdot \gamma \quad (6)$$

Determining the value of γ and cancel its effect conduct the chromatic representation, like is shown in equation (7).

$$\left(\frac{r \cdot \gamma}{r \cdot \gamma + g \cdot \gamma + b \cdot \gamma}, \frac{g \cdot \gamma}{r \cdot \gamma + g \cdot \gamma + b \cdot \gamma}, \frac{b \cdot \gamma}{r \cdot \gamma + g \cdot \gamma + b \cdot \gamma} \right) = \left(\frac{r}{r + g + b}, \frac{g}{r + g + b}, \frac{b}{r + g + b} \right) \quad (7)$$

The chromatic representation is produced with $\left(\frac{r}{r + g + b}, \frac{g}{r + g + b}, \frac{b}{r + g + b} \right) = (r_c, g_c, b_c)$ and then parameter γ can be determined with equation (8) using equally done red, green or blue colors.

$$\gamma = \frac{r}{r_c} = \frac{g}{g_c} = \frac{b}{b_c} \quad (8)$$

Despite though γ can control luminosity there are different values that can be allowed to be brown instead of black since both of them are in a near region of luminosity and similarly can be found values that are consider blue instead of white in the high regions of luminosity. In that sense the ranges must be verified for all the values of r , g and b in colors black and white. With that in mind the proposed model in this work for identifying black and white colors are those in (9) and (10) respectively, requiring only three parameters per color since they are in the lower and upper boundaries of the RGB space.

$$(\alpha_1 \leq r) \wedge (\alpha_2 \leq g) \wedge (\alpha_3 \leq b) \quad (9)$$

$$(\alpha_1 \geq r) \wedge (\alpha_2 \geq g) \wedge (\alpha_3 \geq b) \quad (10)$$

The next step is to determine the values of all the parameters α_n these are obtaining by setting $\mathbf{X}_i = \langle \alpha_1, \dots, \alpha_n \rangle$ for each of the colors, obtaining $\mathbf{X}_i \in \mathbf{R}^3$ for black and white colors and $\mathbf{X}_i \in \mathbf{R}^6$ for the rest of the colors. After that \mathbf{X}_i is substituted in the PSO algorithm then the cost function in equation (11) is used in the algorithm 1 like is described in [12].

$$F(\mathbf{X}_i) = \frac{1}{H \cdot W} \sum_{m=1}^H \sum_{n=1}^W |out_d(m, n) - out(m, n)| \quad (11)$$

with H and W defined as the height and width of the image, out_d is the desired output for classifying the color and out is the input image like is described in [12].

3.2 Classifying security signs

The security signs have dominant colors related to the kind of signs like is described in section 1 but also have secondary colors, with that in mind after that equations (1), (2), (3), (9) and (10) are tuned for the desired colors these are related to an specific security sign depending from its primary and secondary color, like is described in the used colors in table 2. In that sense security signs are classified as in equation (12).

$$SC(C_1, C_2) = \begin{cases} \text{Forbidden,} & (C_1 = red \vee black) \wedge (C_2 = red \vee black) \\ \text{Required,} & (C_1 = blue \vee white) \wedge (C_2 = blue \vee white) \\ \text{Warning,} & (C_1 = yellow \vee black) \wedge (C_2 = yellow \vee black) \\ \text{Information,} & (C_1 = green \vee white) \wedge (C_2 = green \vee white) \end{cases} \quad (12)$$

3.3 Augmented Reality Labeling

The labeling of the data is saved in an image P that is obtained by acquiring an image from the digital camera denoted by Im_d and then process it using the equations for color classification described in section 2 and 3, since all of them are logical equations the result is a logical image L_k per color showing 1 if color condition is satisfied or 0 if not, with k as a color index related to the nine possible colors to classify, after that if conditions in equation (12) are satisfied for a kind of sign then that sign is wise multiplied by image A_l that contains the form symbols related to the kind of security signs shown in table 2, and l is the index associated to the number of security sign type, the obtained value is subtracted from original image creating a water mark label, like is shown in equation (13).

$$P = Im_d - 0.1(L_k \otimes A_l) \quad (13)$$

4 Experimental Design

The training part using PSO is performed by using the data set for color classification and validation for nine colors obtained from [21]. Original Dataset has 107 training images distributed with 14 images for black, 10 images for blue, 20 images for brown, 7 images for green, 10 images for orange, 10 images for red, 10 images for violet, 16 images for white and 10 images for yellow, and has 96 images for validation, but in this paper there are added 4 new images for validation of brown color obtaining a total of 100 validation images.

Dataset training images are modified by putting pixels that belongs to the classified color in zero for the desired training image out_d , this modification is performed for the nine classified colors, after that training is complete with PSO algorithm then the results of training are tested with validation images and the is obtained the summing of all pixels labeled per color (px_c) in output images like in equation (14).

$$px_q = \sum_{m=1}^H \sum_{n=1}^W out(m, n) \quad (14)$$

with q as the corresponding index for the classified color.

Then the C_1 and C_2 colors are obtained and verified in the validation images, this is performed by taking a validation image, processing it and checking it if effectively C_1 and C_2 are the primary and secondary colors in the validation image.

After that training of colors is complete the same process of validation is tested with the results of equation (12) using security signs of a dataset built in this work with 10 security signs per type of sign, for a total of 40 validation signs.

All the obtained results are processed in a computer with Microsoft Windows 10 Pro, Intel(R) Core (TM) i3-4150 CPU @ 3.50GHz processor, 8.00 GB RAM memory and a NVIDIA GeForce GTX 950 video card.

5 Results

In this section are presented the results obtained while training color dataset its validation, and validation on the detection of the security signs, finally are presented images labeled using AR methodology described in section 3.

5.1 Results of training dataset

PSO configuration parameters were adjusted heuristically until obtaining good response with a good relation between exploration and exploitation of the search space.

The parameters used for all the 9 colors in the PSO algorithm are shown in table 4.

Table 4 Parameters used in the PSO algorithm.

PSO parameter	Value	Description
\max_t	200	Number of iterations used.
w	1.5	Inertial parameter (initialized to this value and then reduced 1% per iteration).
c_1	2	Personal component.
c_2	2	Social component.
D	6	Dimensions, 3 values ignored in white and black.
Max \mathbf{X}_i	1	Maximum possible position.
Min \mathbf{X}_i	-1	Minimum possible position.
Max \mathbf{V}_i	0.4	Maximum velocity.
Min \mathbf{V}_i	-0.4	Minimum velocity.
Particles	200	Number of particles used.

The results of PSO algorithm obtained per color are exhibit from Figure 2 to Figure 9, showing the cost function response across iterations.

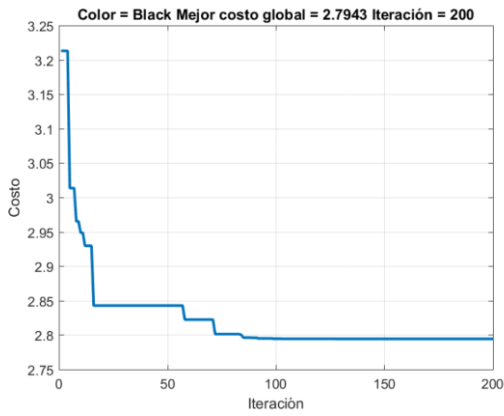


Figure 2 $F(X_i)$ across iterations training black color.

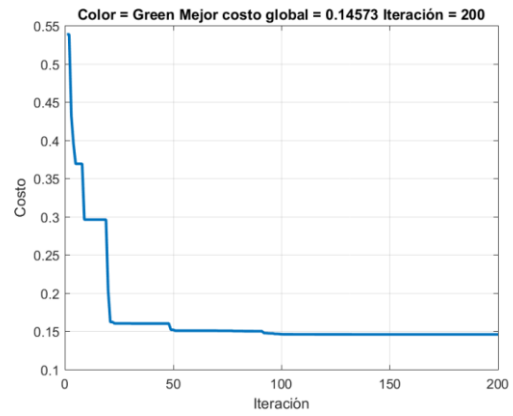


Figure 5 $F(X_i)$ across iterations training green color.

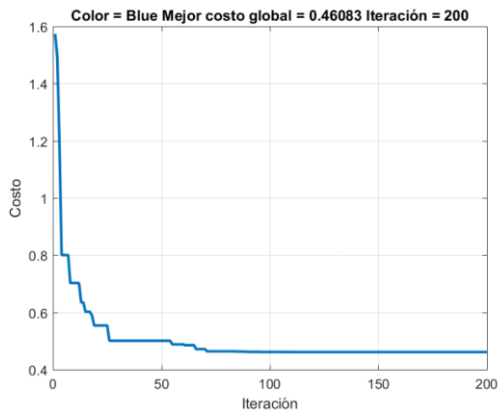


Figure 3 $F(X_i)$ across iterations training blue color.

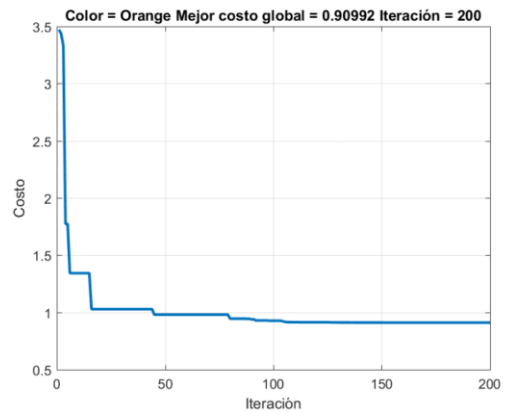


Figure 6 $F(X_i)$ across iterations training orange color.

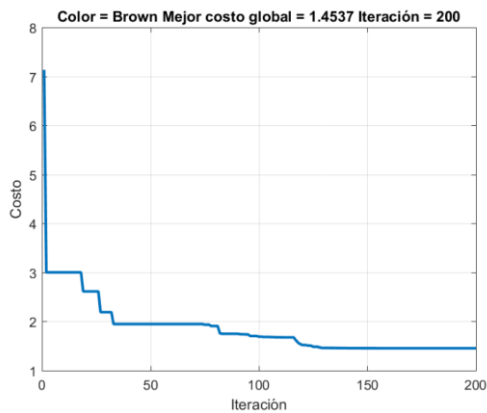


Figure 4 $F(X_i)$ across iterations training brown color.

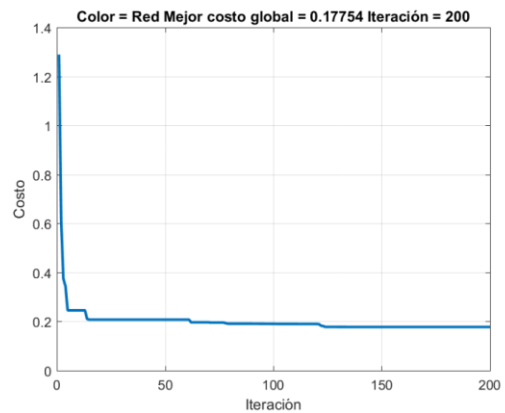


Figure 7 $F(X_i)$ across iterations training red color.

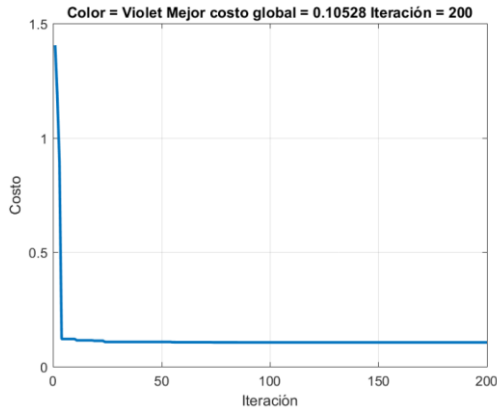


Figure 8 $F(\mathbf{X}_i)$ across iterations training violet color.

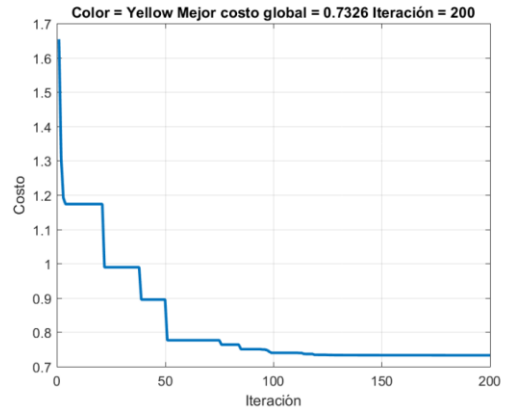


Figure 10 $F(\mathbf{X}_i)$ across iterations training yellow color.

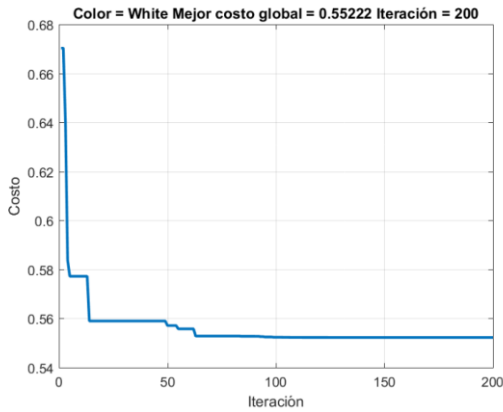


Figure 9 $F(\mathbf{X}_i)$ across iterations training white color.

5.2 Results of validation of color classification

Table 5 shows the effectiveness reached in color classification with the validation images in color dataset.

Table 5 Efficiency obtained identifying primary and secondary colors in the validation images of color dataset.

Color Classified	Positive Corrects	Efficiency
Black	10/10	100%
Blue	12/12	100%
Brown	6/6	100%
Green	12/12	100%
Orange	12/12	100%
Red	13/13	100%
Violet	11/11	100%
White	12/12	100%
Yellow	12/12	100%
Total for all colors	100/100	100%

The Table 6 shows the effectiveness reached classifying security signals with the proposed methodology.

Table 6 Efficiency classifying security signs.

Security Sign Classified	Positive Corrects	Efficiency
Forbidden	10/10	100%
Required	10/10	100%
Warning	10/10	100%
Information	10/10	100%
Total for all colors	40/40	100%

5.2 Results of AR labeling

Some of the security sign images in dataset are shown from Figure 11 to Figure 14, comparing the original image, processed image and labeled AR image using the methodology described in section 4.



Figure 11 Warning sign labelled with proposed technique.

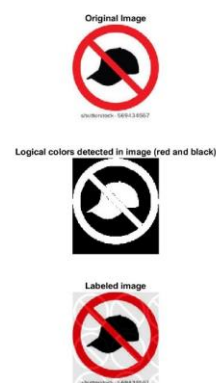


Figure 13 Forbidden sign labelled with proposed technique.

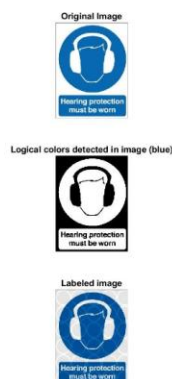


Figure 12 Required sign labelled with proposed technique.



Figure 14 Information sign labelled with proposed technique.

The final AR labeled images are obtained in an average of 0.15 seconds in pictures of 521×521 pixels using GPU parallelizing with the video card described in section 4.

6 Conclusions

This paper presents a proposed methodology for classifying and performing AR labeling of security signs for assisting colorblind people using linear equations optimized with a PSO algorithm, the model for color classification reaches 100% of efficiency identifying the primary and secondary colors in a dataset of 100 validation images.

The classification of signs also reaches a 100% of efficiency validated in a dataset of 40 images with security signs, but this dataset should be extended for better validation, however if efficiency decreases in the identification of security signs then color segmentation should be adjusted by adding training images with more data about the colors that should be classified.

Despite that linear proposed equations and the equations used from [12] exhibit good results, in future works should be tested non-linear equations that can be obtained using automatic programming techniques like is used Genetic Programming in [22].

In several situations in industrial environments is not possible to use the AR assistant with nowadays devices, however it should be used for the training stage in a new job position where security signs with regulations like those in the NOM-026-STPS-1998, in order to simplify the learning curve for colorblind people.

6.1 Future work

In the next stage the proposed algorithm should be adapted for working in mobile devices that would be used by colorblind people during the training stage in places regulated with security signs like those in NOM-026-STPS-1998.

For improving recognizing capabilities new equations should be obtained with automatic programming techniques like is done in [22], in order to assure the best performance in the proposed assistant.

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