

Implementation of a system for classifying moving parts by color

Implementación de sistema para la clasificación de piezas en movimiento por color

RODRÍGUEZ-FRANCO, Martín Eduardo†*¹, LÓPEZ-ÁLVAREZ, Yadira Fabiola¹, JARA-RUIZ, Ricardo¹ and OROZCO-SOTO, Santos Miguel²

¹Universidad Tecnológica del Norte de Aguascalientes, Rincón de Romos, Aguascalientes, México

²University of Naples Federico II, Naples, Campania, Italy

ID 1st Author: *Martín Eduardo, Rodríguez-Franco* / **ORC ID:** 0000-0002-6804-4777, **Researcher ID Thomson:** T-1539-2018, **CVU CONACYT ID:** 660892.

ID 1st Co-author: *Yadira Fabiola, López-Álvarez* / **ORC ID:** 0000-0002-9041-1908, **Researcher ID Thomson:** T-1555-2018, **CVU CONACYT ID:** 375952

ID 2nd Co-author: *Ricardo, Jara-Ruiz* / **ORC ID:** 0000-0001-7725-4138, **Researcher ID Thomson:** T-1532-2018, **CVU CONACYT ID:** 630276

ID 3rd Co-author: *Santos Miguel, Orozco-Soto* / **ORC ID:** 0000-0001-6191-4306

DOI: 10.35429/JSI.2022.18.6.1.10

Received March 14, 2021; Accepted June 29, 2021

Abstract

The purpose of this study is the development and implementation of a computer vision system for color identification in a set of parts, which were disposed on a continuously moving conveyor belt. The process for acquiring the images associated with the parts at issue, the preprocessing and treatment phases performed, as well as the results of the recognition of the feature of interest in each of these are exposed. It is worthy to mention that the feature of interest in the analyzed parts was established from three classes different, associated with the primary colors. The results obtained suggest the effectiveness of the implemented vision system, even as a prototype; which was integrated using low-cost and easy-to-use materials, and whose programming was developed in the open-source software Python, using the OpenCV library. Not only an effective recognition of the class corresponding to each part entered is highlighted, but also the possibility that said operation be executed without the conveyor belt used stopping its moving.

Computer vision, Color identification, Moving parts tracking

Resumen

El presente estudio tiene por propósito el desarrollo e implementación de un sistema de visión por computadora para la identificación del color en un conjunto de piezas, las cuales fueron dispuestas sobre una banda transportadora en movimiento continuo. Se expone el proceso para la adquisición de las imágenes asociadas a las piezas en cuestión, las fases del preprocesamiento y tratamiento ejecutados, así como los resultados del reconocimiento de la característica de interés en cada una de éstas; misma que fue establecida a partir de tres clases distintas, asociadas a los colores primarios. Los resultados obtenidos sugieren la efectividad en el funcionamiento del sistema de visión implementado, aun como un prototipo; el cual fue integrado empleando materiales de bajo costo y fácil manejo, y cuya programación fue desarrollada en software de código abierto: Python, y la librería OpenCV. Se resalta, no únicamente un reconocimiento efectivo de la clase correspondiente a cada pieza ingresada, sino la posibilidad de que dicha operación sea ejecutada sin que la banda transportadora utilizada detuviera su recorrido.

Visión por computadora, Identificación de color, Seguimiento de piezas en movimiento

Citation: RODRÍGUEZ-FRANCO, Martín Eduardo, LÓPEZ-ÁLVAREZ, Yadira Fabiola, JARA-RUIZ, Ricardo and OROZCO-SOTO, Santos Miguel. Implementation of a system for classifying moving parts by color. Journal of Systematic Innovation. 2022. 6-18: 1-10

* Correspondence to Author (e-mail: martin.rodriguez@utna.edu.mx)

† Researcher contributing as first author.

Introduction

In recent decades, the evolution of inspection systems has left aside manual tasks, performed by people, to focus on the use of the computer as a means for the automatic execution of such a function (Xiao-bo, Jie-wen, Yanxiao, & Holmes, 2010) (Patel, Kar, Jha, & Khan, 2012). From this fact, various industrial activities have benefited, including the selection of fruits and vegetables (Vijayarekha, 2012) (Zhang, y otros, 2014), food safety assurance (Dowlati, de la Guardia, & Mohtasebi, 2012) (Jackman & Sun, 2013) and, the manufacturing and assembly of mechanical elements (Barari, 2013) (Ayub, Mohamed, & Esa, 2014), among others. Thus, automatic inspection systems are developed from the application of artificial vision techniques, which encompasses the study of methods for understanding and encrypting an analyzed image, from a computer, in order to obtain certain characteristics. that are of interest (Santos-Gomes & Rodrigues-Leta, 2012). In this way, a computer vision system can be considered as an integration of mechanical elements, sensors and instrumentation, digital video systems and image processing techniques (Patel, Kar, Jha, & Khan, 2012).

On the other hand, image preprocessing includes the use of operations to improve its quality, through noise reduction, contrast improvement and the definition of captured shapes (Kodagali & Balaji, 2012). After preprocessing, the segmentation, description and recognition of individual objects present in the captured image are necessary, from the extraction of study attributes, such as edges, contours, areas, etc. Finally, the application of cognitive functions, associated with vision, is required to provide a sense to the recognized object as a whole (Xiao-bo, Jie-wen, Yanxiao, & Holmes, 2010).

It is worth mentioning that, at present, various industrial operations perform automated inspection tasks of processed parts on a moving conveyor belt. Such an attachment is one of the main components of a typical material handling system (Bozma & Yalçın, 2002), on which objects are briefly positioned to be transported between two different points of a production process (Selver, Akay, Alim, Bardakçı, & Ölmez, 2011). By means of a camera, usually placed above the conveyor, that each object that moves along it is visualized (Tran, 2019).

Motivation

Given the relevance of computer vision systems in the current industrial environment, and particularly, of its application as a central element in automated inspection, it is of great interest in the technological academic field, the study of the elements that comprise it, as well as the role they perform together. Such is the importance conferred to these systems, which are part of the subject topics for various Engineering profiles; therefore, an exploration in great detail of their capabilities can bring with it knowledge of their functionality, prior to having contact with them in the industry.

However, since having a vision system with the features of those used in large transformation companies, means a heavy expense, it is possible to resort to the creation of a prototype, made up of elements that are easy to use, low cost and with acceptable performance. Likewise, based on the evolution of computing and the proposal of increasingly competitive programming languages and specialized libraries, it is possible to develop sophisticated artificial vision algorithms, without resorting to complex equipment or high processing demand, but that they can be executed from a personal computer.

Additionally, the process of designing the functionality of a vision system for automated inspection purposes implies understanding its structuring phases, starting from its base elements: software and hardware. Therefore, the need and challenge of conforming both the physical portion, as means for image acquisition, and developing its virtual counterpart, to ensure the processing of these and the extraction of the useful characteristics for the analysis undertaken, is assumed. In this way, the proposed process can encompass a set of tasks that enrich the experience of the participants.

Conveyor belt prototype

The conveyor belt used, shown in figure 1, was created from two side walls manufactured in rectangular hollow sections (RHS); at whose ends are located the supports that give them height.

The separation between walls was established by metal rollers screwed to them; one of which allows the tension adjustment of the belt itself. The belt used is made of black rubber, whose ends were joined to form a closed loop. Likewise, a direct current electric motor with mechanical reducer is used, powered at 12 V; which is attached to one of the end rollers of the band to induce movement, at a rate of 0.157 ft./s (0.048 m/s).

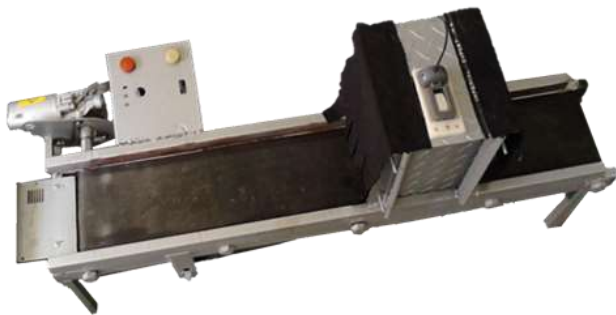


Figure 1 Conveyor belt used
Source: Own Elaboration, 2022

An inspection area has been adapted to the conveyor described, consisting of two walls and a flap, made of sheets of steel sheet, and joined together. The walls were welded to those of the band, from four steel angle bars, which also support the upper portion. On the latter, a base was adapted for the location of the camera, being manufactured in polylactic acid (PLA) by 3D printing. Curtains were placed on the open ends, whose function is to allow parts access to the inspection area, while it remains isolated from external lighting.

Structure and function of vision systems

A computer vision system is mainly made up of five basic elements: lighting, camera, image capture card, software and hardware, as shown in figure 2. Other complementary elements to the vision system can be image filters and the guided means for the transportation of the digitized image and the communication between devices (Dowlati, de la Guardia, & Mohtasebi, 2012) (Zhang, y otros, 2014).

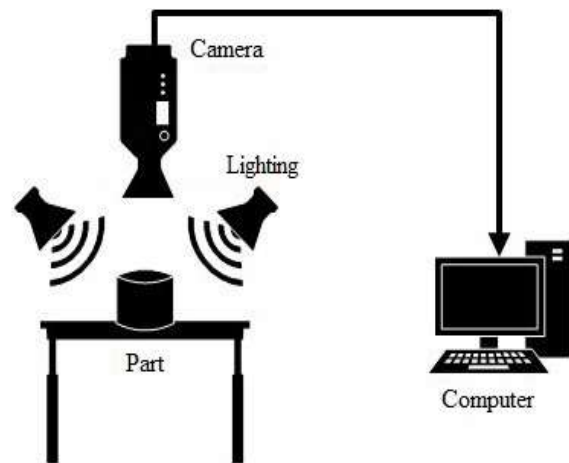


Figure 2 Computer vision system structure
Source: Own Elaboration, 2022

The camera is the main component of the vision system, performing image acquisition. The captured image is a matrix of tiny photosensitive elements; whose shutter is proportional to the amount of incident light. An image capture card is used to identify the frame of an object, and then store it in a compressed form (Wu & Sun, 2013). Meanwhile, the hardware and software work together for the analysis of the acquired image, the extraction of the features of interest and the execution of the classification task. Such actions are similar to those performed by the human brain (Ayub, Mohamed, & Esa, 2014) (Wang, Wang, Chen, & Xu, 2018).

Similar to human eyes, computer vision systems are affected by the level and quality of lighting. Such property is applied to the objects to be inspected, therefore, the control in the intensity and effectiveness of the lighting system used, determines, in turn, the effectiveness in the processing of the acquired images (Wang, Wang, Chen, & Xu, 2018), by reducing disturbances inherent to this process (Kodagali & Balaji, 2012).

The main interest of the processing and analysis of the images, obtained from the application of a computer vision system, is to constitute an informative, significant and explicit description of the physical object of interest (Brosnan & Sun, 2004) (Dowlati, de la Guardia, & Mohtasebi, 2012). For which, algorithms will have to be developed and applied that allow the subsequent execution of object classification or measurement tasks (Ye, Dong, & Liu, 2016), through the fulfillment of the following stages:

1. Acquisition of images and their conversion to a digital format.
2. Improvement of the characteristics of the image for its pre-processing.
3. Segmentation of the digital image to separate non-overlapping regions.
4. Obtaining the characteristics of the object of interest in the image.
5. Classification for the identification of the object through groups of classes.

Operation of the proposed system

The proposed computer vision system will have to identify the color and area attributes of the parts that are placed on a first end of the used conveyor belt. Each part deposited on the belt will be taken inside the inspection area, and when detected by the camera, a contour will be drawn on its edge, of the respective color.

This contour represents the result of the visual classification executed on each part entered, based on the feature of color; being established three categories: red, green and blue. It should be noted that the conveyor will never stop moving.

Thus, when executing the capture of images corresponding to the parts on the moving belt, the camera will play a vital role for the implemented vision system. In this case, it is a Genius FaceCam 321 model camera, shown in figure 3, whose specifications are presented in table 1.

The focus of such camera has been oriented inside the confined space by the inspection cabin, adapted above the belt. The focal point of the camera was placed at a horizontal distance of 4.331 in (11 cm) and a vertical distance of 4.134 in (10.5 cm), both with respect to the lower left corner that forms the roof of the cabin used.



Figure 3 Genius FaceCam 321 camera
Source: <https://us.geniusnet.com>, 2022

Feature	Specification
Weight	1.764 oz (50 g)
Height	2.362 in (6 cm)
Width	1.772 in (4.5 cm)
Depth	1.575 in (4 cm)
Software	Arcsoft WCC4 Lite Arcsoft MiVE Genius Utility
Minimum processor	Intel/AMD 1.6 GHz
Minimum RAM	512 MB
Interface	USB 2.0
Sensor type	CMOS
Mounting type	Clip/Stand
Digital zoom	3X
Resolution	8 Mpx
Video formats supported	M-JPEG, WMV
Maximum video resolution	640 x 480 px
Maximum frame rate	30 pps

Table 1 Technical details of Genius FaceCam 321 camera
Source: <https://us.geniusnet.com>, 2022

As the camera was placed above the inspection compartment, in addition to being viewed at a vertical distance of 0.886 ft. (27 cm) above the conveyor belt, it was possible to establish a 0.656 x 0.525 ft. (20 x 16 cm) surface captured by the shot. Therefore, it should be noted that the aforementioned area exclusively ensures the visualization of the portion of the belt and, once the corresponding tests have been performed, the appreciation of each of the objects that move through it. Such a ratio was determined by the focal length between the camera lens and its field of view.

Likewise, in order to preserve the adequate lighting conditions for color recognition in the parts to be processed, cold white light-emitting diodes (LEDs) were adapted inside the inspection space.

These devices were located in proximity to the upper corners inside the cabin, so that their orientation allows the lighting to be assigned and uniformly affect the upper face of each part entered. This decision was made given that, since the upper face of the parts is fully captured by the camera, this will be the reference for the subsequent processing that will be executed on the acquired image.

Algorithm for part classification

The preparation of the inspection cabin, the establishment of the camera capture area, and the calibration of the lighting system used, allowed to continue with the development of the visual classification algorithm of parts, as well as the performance of the initial tests on them in order to validate its effectiveness. It will be common that in the image analysis and processing sections, the term “object” be used to refer to the area of interest detected and that stands out from the background in a specific image; unlike “part”, which will refer to the physical element of interest, in which the features from which this analysis is applied converge.

The algorithm used for the classification of parts was programmed in the Python Integrated Development and Learning Environment (IDLE), through functions from the OpenCV library, whose purpose is the acquisition and processing of images and video. The flow in the developed programming includes the stages shown in figure 4.

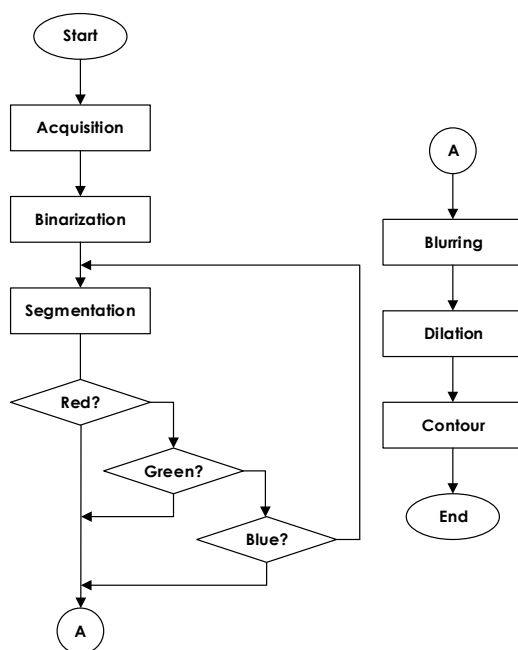


Figure 4 Algorithm for part classification by color

Source: Own Elaboration, 2022

Image acquisition

Image acquisition is determined by light reflected, transmitted or emitted from the beam arrangement received by the camera and radiation from the illumination system, which can illuminate, transmit through, reflect or absorb after interacting with the object studied (Zhang, y otros, 2014). Therefore, having a space that is properly isolated from the outside and uniformly lit is critical for this process. It is worth mentioning that the surface defined for the camera focus, and that frames the width of the belt, ensures the capture of any point on it; where a particular disposition of each part to be analyzed is not required; as highlighted in figure 5. It is even possible that the analyzed part adopts any orientation on the belt, without this affecting the effectiveness of subsequent processing.

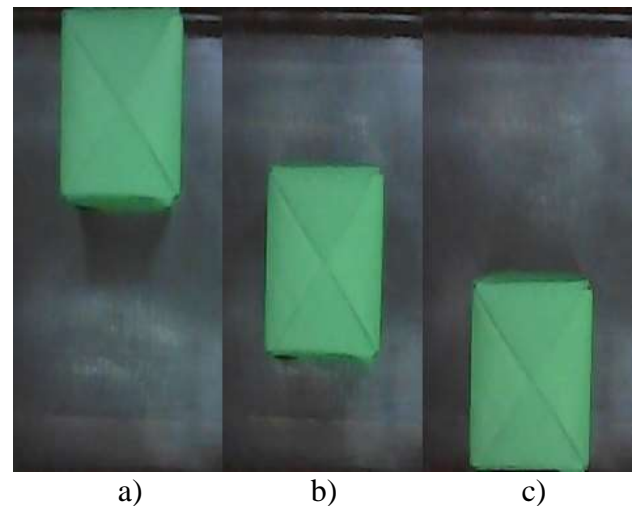


Figure 5 Part capture on the belt at: a) upper end, b) center and c) lower end

Source: Own Elaboration, 2022

Image binarization

The preprocessing of each acquired image begins with the binarization or thresholding operation, which distinguishes only two classes in a captured image: the object of interest and the background that contains it. This process is based on the imposition of a threshold intensity value, from which the portions of the image with an intensity equal to or greater will be represented completely white, while those below will appear black. Such an operation confers the features of computational simplicity, high speed and zero complications in its implementation (Tavakoli & Najafzadeh, 2015).

In this case, it is intended that the black color corresponds to the background that surrounds the part of interest, while the white is assigned to the surface of the latter, highlighting it from the rest of the captured image. However, it is necessary to mention that, by submitting three different colors of the part to the analysis, three different options were determined for the identification of each color, which leads to distinguish one part from another by means of such an attribute.

Object segmentation

Segmentation divides a binarized image into various regions, by highlighting the object of interest from its background, with the aim of extracting its own features (Brosnan & Sun, 2004). Thus, for the purposes of the exposed analysis, the segmentation allows the proposal, by the user, of the maximum and minimum values per component of the RGB spectrum, for the distinction of the part from the rest of the image captured by the camera. For which, the gradual modification of each color component (red, green or blue) was performed; starting by removing those that do not suggest a great presence in the analyzed part. For the success of the aforementioned operation, within the algorithm, the visualization of the analyzed object was programmed on an alternate screen, once binarized, as well as a set of bars that allowed the user to directly modify the conditions for the segmentation of each part, according its color; as can be seen in figure 6. The slider bars used, whose values range from 0 to 255, indicate the shade of the color to be identified, from its lowest or darkest point to its highest or brightest point, depending on the primary component to be affected.

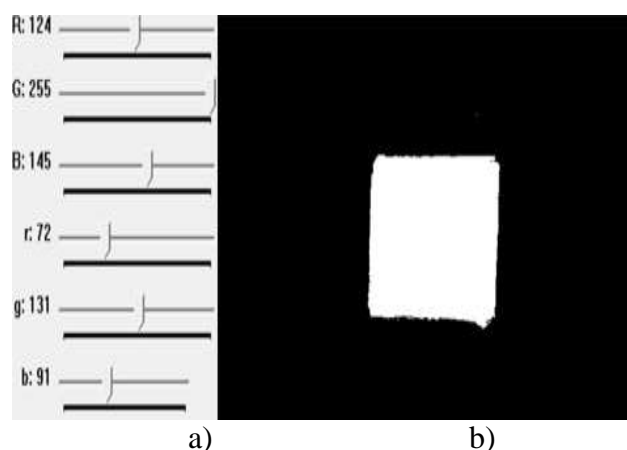


Figure 6 Green part segmentation: a) proposed values and b) aspect

Source: Own Elaboration, 2022

This operation was applied differently for each part analyzed, since the levels proposed for the detection of a specific color would be dissimilar from those necessary for the recognition of any of the other two identifiable ones. Likewise, from the execution of an adequate operation, it can be ensured that if a part, with a different color, is placed near to another whose color has been previously segmented, the vision system ignores the attributes of the first. This effect is due to, as it does not belong to the segmented color group, the system interprets any other part as a portion of the background in the captured image.

It is worth mentioning that, if during the segmentation of any of the proposed class colors, an excessive withdrawal is exerted on any of their components, it is possible that there is a loss of substantial information in the analyzed part. Such a situation can lead to an inadequate interpretation of the information established by the processing, as shown in figure 7. In this figure, an incomplete determination of the area corresponding to the represented part can be seen, which would negatively affect the subsequent phases of the analysis performed.

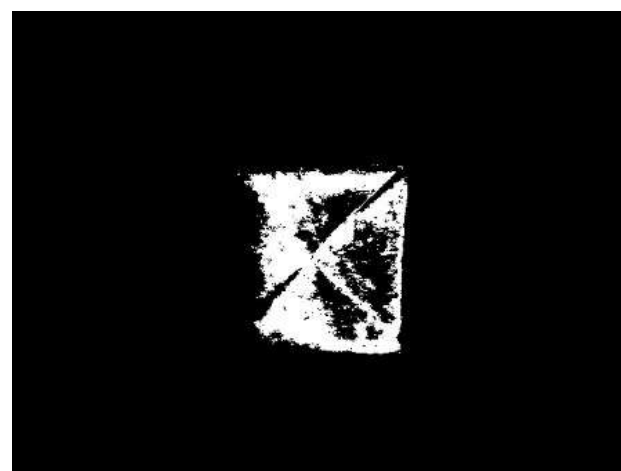


Figure 7 Loss of part information

Source: Own Elaboration, 2022

After completing the segmentation process on each specific class, within the initially proposed categorization, the quantities given in table 2 are determined, in which the minimum and maximum values respectively used to identify the color of the analyzed part are shown. It should be noted that the exclusive use of each pair of values allows the identification of parts with the indicated color, seeking at all times to eliminate possible overlaps between sets that lead to interpreting one color as another.

Part Color	R		G		B	
	Component Min.	Component Max.	Component Min.	Component Max.	Component Min.	Component Max.
Red	183	255	83	160	87	163
Green	72	124	131	255	91	145
Blue	44	124	74	177	188	255

Table 2 Values set for color targeting
Source: Own Elaboration, 2022

Blurring operation

The blurring operation allows the smoothing of the edges that define an object analyzed in a specific uniform background. Therefore, if there are cavities or irregular regions in the captured object, which do not exist in the real part, they could well be eliminated by means of this operation, or at least they would acquire a more homogeneous appearance. Such an action is possible by averaging the colors of a specific pixel and some of its neighboring pixels (Du & Sun, 2004).

Thus, after performing the color identification process in each part analyzed, it is possible that, due to the excessive modification of some tonality index, isolated portions of color or noise that do not belong to the set of pixels that represent each detected part be noticed. Such a situation can be inherently caused by trying to preserve substantial information that allows the part to stand out from the background that surrounds it; being necessary the blurring of the captured image.

Dilation operation

Smoothing the edges of an object, from the blurring process, could result in an irregular entity that does not retain the shape, proportions, or sizing of the original part. Therefore, it is decided to increase the region of the analyzed object, by means of the dilation operation (Patel, Kar, Jha, & Khan, 2012). This operation would not only provide a solid and uniform appearance in the processed object, but also the cavities or hollows caused by previous operations can be eliminated, as they are “absorbed” by the action of dilation. Continuing the processing executed, the application of the dilation operation seeks, as much as possible, to generate a processed part with an appearance very similar to the original, which may be evident in the shape of the outer contour that distinguishes it from the background.

This limit between pixels of two different classes, will highlight the final contour of the processed part for its identification, not only of the background that surrounds it, but of other parts in different colors, which can be captured at the same time, by the camera, on the belt.

Part contour

Post-processing, feature extraction defines a set of attributes that meaningfully represent information that is important for analysis and classification of a studied object. The most commonly analyzed features are color, shape and texture (Patel, Kar, Jha, & Khan, 2012). Thus, feature selection algorithms base their function on the establishment of properties that allow adequately defining the attribute of interest for the study, which, after processing, can be located in the contour or region of the analyzed object (Makem, Ou, & Armstrong, 2012).

In this case, after establishing the region associated with the area occupied by the processed part, for each color, it was necessary to draw a contour that would fix the identified surface of the background or of some other part that could be captured by the camera. In addition, the customization of the established contour was done, based on the designation of a specific thickness and color; where the latter alluded to the color detected in the part captured in particular.

Part classification results

The formation of images through the camera used, as well as the application of techniques for their pre-processing, allowed to characterize each part of interest, based on its color, distinguishing it from the background, regardless of whether they were in motion. In particular, the function of segmentation in estimating the necessary parameters for the identification of each component of the RGB spectrum, present in each analyzed part, through binarization, is highlighted.

Thus, as a result of the segmentation, executed on each proposed class, it was possible to establish the quantities specified in table 2, which represent the minimum and maximum values necessary for the adequate identification of the color of each analyzed part.

Therefore, the exclusive use of each pair of given values allows the characterization of the parts in the respective color, indicated in the table itself; considering the elimination of any overlap between tonal sets, which leads to interpreting a color as a different one.

It should be noted that, based on the given values, it was also possible to adequately identify each of the three possible color classes in an analyzed part, independently, even in the presence of objects belonging to the remaining classes. Such an effect can be verified in figure 8, in which a respective part of each class is characterized, close to elements corresponding to the other two analyzed, without this fact affecting the effectiveness of the identification task, depending on the color.

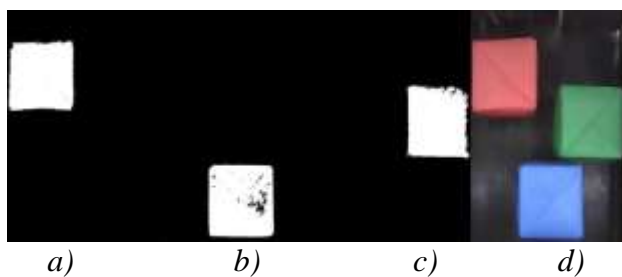


Figure 8 Segmentation by class: a) red, b) blue, c) green and d) acquired image
Source: Own Elaboration, 2022

It is noteworthy that, during the part recognition process, efforts were made to have significant information available that would enable a propitious definition, not only of its color, but also of its physical dimensions; which were particularly related to the region detected for each one. Therefore, the application of blurring and dilation operations was a priority, in order to have an area as uniform as possible, which would represent each part analyzed, and in turn, its limits with respect to the background, as can be seen in the figures 9 and 10, respectively.

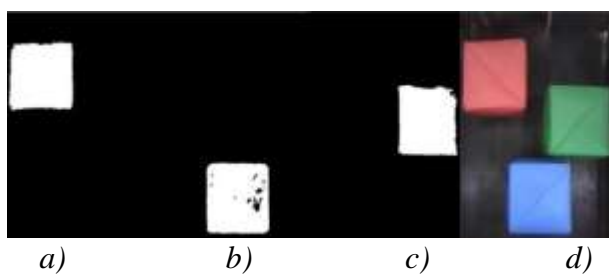


Figure 9 Blurring by class: a) red, b) blue, c) green and d) acquired image
Source: Own Elaboration, 2022

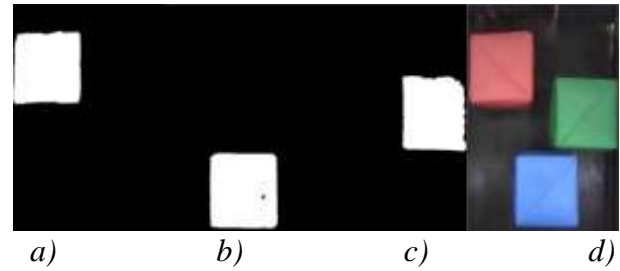


Figure 10 Dilation by class: a) red, b) blue, c) green and d) acquired image
Source: Own Elaboration, 2022

Resuming the identification of parts of a specific class in the presence of those that belonged to a different one, figure 11 shows the imposition of an external contour on each analyzed part. This contour encloses the region that represents the area identified in each part, determined by a set of pixels that share the same color. Finally, figure 12 exhibits the adequate identification of a part for each color, once it describes a movement through the conveyor belt. It is noted that despite the appearance of noise, inherent to the given displacement, the recognition of each part is performed successfully.

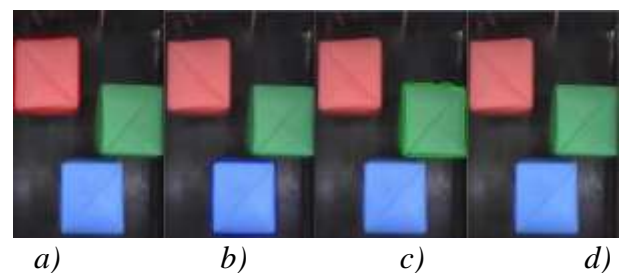


Figure 11 Contour by class: a) red, b) blue, c) green and d) acquired image
Source: Own Elaboration, 2022

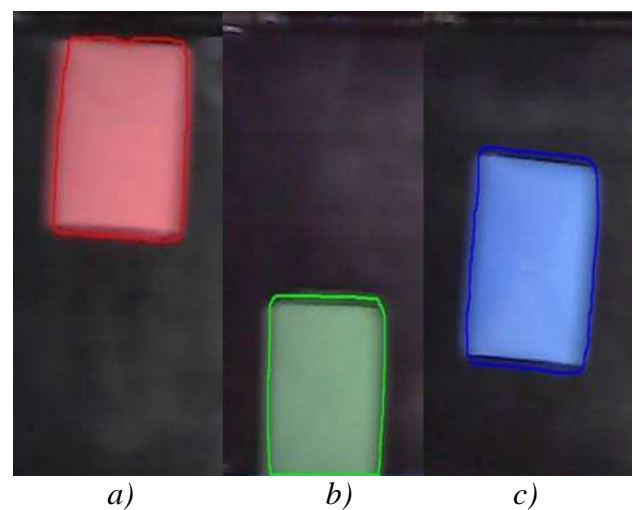


Figure 12 Moving part classification: a) red, b) green and c) blue
Source: Own Elaboration, 2022

Conclusions

Through the acquisition of images and their processing, vision systems enable the recognition of features that are of interest for the execution of specific tasks, commonly the identification and classification of parts. Such functions are especially enhanced when they are performed on parts that prescribe a continuous movement, as analyzed by this work. However, the dynamism provided to the detection process implies a timely solution to inconveniences that may arise, such as: the appearance of noise, the generation of shadows or the formation of clusters of pixels in areas outside the object of interest.

Thus, the mitigation of the negative effects caused by the movement of the studied parts must be sought from the preprocessing phases in order to avoid, as far as possible, the substantial loss of relevant features and, therefore, the inadequate interpretation of the information obtained from the operation itself.

Although, beforehand, it is essential to have adequate lighting to reduce the occurrence of alterations in the capture of a part, which affect negatively its subsequent treatment. Therefore, an effective conduction between the capture of an image and its processing, leads to guaranteeing the full identification of the attributes of interest; as observed in the developed process.

It should be noted that, within the preprocessing, the segmentation operation serves as the basis for the suitable estimation of the pixel region associated with each analyzed part. In this case, the identification and application of the values of the color components in the effective distinction of each class, with respect to another also scrutinized, even in its presence, was a great success; as seen in the reported results.

Even so, the contribution of the blurring and dilation operations, also performed, is not underestimated, since they strengthened the subsequent recognition function, by improving the description of the established regions where the segmentation function was limited, such as gaps and irregularity on the edges.

In this way, and given the operating results obtained from the test of the implemented vision system, the competitiveness achieved by it is validated, even in the case of a prototype. Also noteworthy is the quality of the task performed, through the use of low-cost, easy acquisition and simple handling devices; as well as the development of the required programming, based on open-source software and libraries, which were executed from a personal computer. It should be noted that the functionality achieved can be comparable to that provided by dedicated systems, which are commonly expensive and require a large amount of processing resources.

References

- Ayub, M. A., Mohamed, A. B., & Esa, A. H. (2014). In-line inspection of roundness using machine vision. *Procedia Technology*, 807-816. doi:10.1016/j.protcy.2014.09.054
- Barari, A. (2013). Inspection of the machined surfaces using manufacturing data. *Journal of Manufacturing Systems*, 107-113. doi:10.1016/j.jmsy.2012.07.011
- Bozma, H. I., & Yalçın, H. (2002). Visual processing and classification of items on a moving conveyor: A selective perception approach. *Robotics and Computer-Integrated Manufacturing*, 125-133. doi:10.1016/S0736-5845(01)00035-7
- Brosnan, T., & Sun, D.-W. (2004). Improving quality inspection of food products by computer vision - A review. *Journal of Food Engineering*, 3-16. doi:10.1016/S0260-8774(03)00183-3
- Dowlati, M., de la Guardia, M., & Mohtasebi, S. S. (2012). Application of machine-vision techniques to fish-quality assessment. *TrAC Trends in Analytical Chemistry*, 168-179. doi:10.1016/j.trac.2012.07.011
- Du, C.-J., & Sun, D.-W. (2004). Recent developments in the applications of image processing techniques for food quality evaluation. *Trends in Food Science & Technology*, 230-249. doi:10.1016/j.tifs.2003.10.006

- Jackman, P., & Sun, D.-W. (2013). Recent advances in image processing using image texture features for food quality assessment. *Trends in Food Science & Technology*, 35-43. doi:10.1016/j.tifs.2012.08.008
- Kodagali, J. A., & Balaji, S. (2012). Computer vision and image analysis based techniques for automatic characterization of fruits - A review. *International Journal of Computer Applications*, 1-14. doi:10.5120/7773-0856
- Makem, J. E., Ou, H., & Armstrong, C. G. (2012). A virtual inspection framework for precision manufacturing of aerofoil components. *Computer-Aided Design*, 858-874. doi:10.1016/j.cad.2012.04.002
- Patel, K. K., Kar, A., Jha, S. N., & Khan, M. A. (2012). Machine vision system: A tool for quality inspection of food and agricultural products. *Journal of Food Science and Technology*, 123-141. doi:10.1007/s13197-011-0321-4
- Santos-Gomes, J. F., & Rodrigues-Leta, F. (2012). Applications of computer vision techniques in the agriculture and food industry: A review. *European Food Research and Technology*, 989-1000. doi:10.1007/s00217-012-1844-2
- Selver, M. A., Akay, O., Alim, F., Bardakçı, S., & Ölmez, M. (2011). An automated industrial conveyor belt system using image processing and hierarchical clustering for classifying marble slabs. *Robotics and Computer-Integrated Manufacturing*, 164-176. doi:10.1016/j.rcim.2010.07.004
- Tavakoli, M., & Najafzadeh, M. (2015). Application of the image processing technique for separating sprouted potatoes in the sorting line. *Journal of Applied Environmental and Biological Sciences*, 223-227. doi:10.13140/2.1.2093.0887
- Tran, H. N. (2019). Study on image processing method to classify objects on dynamic conveyor. *Science & Technology Development Journal-Engineering and Technology*, 127-136. doi:10.32508/stdjet.v2iSI2.489
- Vijayarekha, K. (2012). Machine vision application for food quality: A review. *Research Journal of Applied Sciences, Engineering and Technology*, 5453-5458. Obtenido de <https://maxwellsci.com/print/rjaset/v4-5453-5458.pdf>
- Wang, H., Wang, J., Chen, W., & Xu, L. (2018). Automatic illumination planning for robot vision inspection system. *Neurocomputing*, 19-28. doi:10.1016/j.neucom.2017.05.015
- Wu, D., & Sun, D.-W. (2013). Colour measurements by computer vision for food quality control - A review. *Trends in Food Science & Technology*, 5-20. doi:10.1016/j.tifs.2012.08.004
- Xiao-bo, Z., Jie-wen, Z., Yanxiao, L., & Holmes, M. (2010). In-line detection of apple defects using three color cameras system. *Computers and Electronics in Agriculture*, 129-134. doi:10.1016/j.compag.2009.09.014
- Ye, X. W., Dong, C. Z., & Liu, T. (2016). A review of machine vision-based structural health monitoring: Methodologies and applications. *Journal of Sensors*, 1-10. doi:10.1155/2016/7103039
- Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J., & Liu, C. (2014). Principles, developments and applications of computer vision for external quality of fruits and vegetables: A review. *Food Research International*, 326-343. doi:10.1016/j.foodres.2014.03.012