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Research Paper

Colour sorting of translucent samples

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Abstract

Automated quality control and sorting based on computer vision techniques has been a long celebrated practice in industrial processes and production. Among the surface characteristics that guide the decision making in such systems, the colour holds a prominent position. This gets somehow complicated in cases dealing with translucent samples or samples with a significant amount of transparency and yet distinctive colour hues. The scope of this paper is to provide a method to tackle with such cases and presents a successful application to the world-renowned mastiha of Chios, a natural aromatic translucent resin extracted from the mastic tree that grows on the island of Chios, Greece.

Keywords: *Colour sorting; Quality control; Computer vision; Translucent samples; Transparency; mechatronics*

1. Introduction

Imaging equipment and enhanced computer vision algorithms have successfully been applied in the industry over the past decades and this tendency keeps rising with the technological advances. These approaches can be effectively introduced in a production line to increase the efficiency of automated processes in various cases. Such applications include mechatronics and robotics, automated guidance, non-destructive inspection, samples monitoring, quality control and sorting, and more. The wide range of applications is due to the nature of computer vision that provides image-based decision making solutions in real-time applications, able to exploit information otherwise not available to humans (multispectral imaging, microscopy, etc). The inspection of food products and specifically the automatic inspection of vegetables and fruits is an area of applications that this technology has spread rapidly with impressive results. These developments have been active for many decades and have provided the industry with numerous successful systems that boosted the large scale production [1–19]. In these developments, a series of physicochemical characteristics define the overall real and apparent quality of fruits and vegetables, which make them more or less attractive for consumption. Predominant among these properties are the maturity, size, weight, shape, colour, presence of dirt and diseases, presence or absence of stem, presence of seeds, sugar content [20]. These features cover all the factors that influence the appearance of a product and may eventually include nutritional and sensory qualities or properties related to its conservation. Most of these factors had traditionally been evaluated by visual inspection performed by qualified personnel. Today this practice has been replaced (to an extent) by commercial automatic inspection systems based on computer vision and image analysis [9]. Human manual sorting processes involve a relatively high risk of error, as decisions can be affected by psychological factors such as fatigue or habits. In addition, it should be noted that automated inspection of agricultural products exhibits some peculiarities due to the biological nature of the inspected samples, which show a wide variety of characteristics, such as a different colour, size and shape, even if collected on the same day from the same tree; Furthermore, such products naturally evolve after harvesting, through a process that changes their colour and texture as time passes. These variations are not to be confused by the presence of stems, leaves, dirt or any foreign material on quality control lines, but

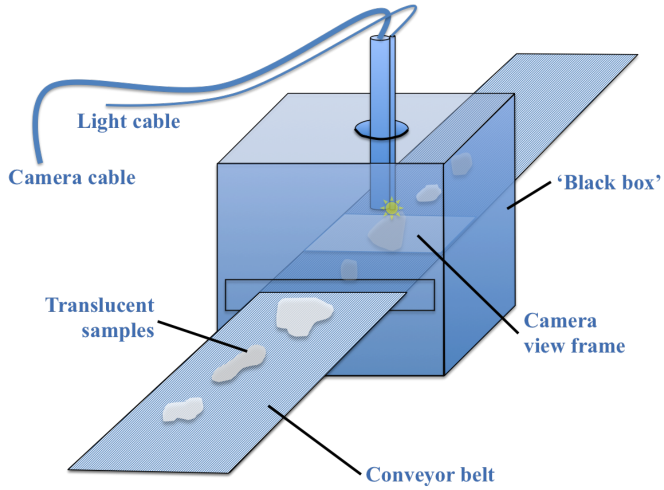

Figure 1: Representation of the prototype setup

should not be neglected also. The nature and parameters of the problem show that the development of algorithms capable of extracting quality decisions from image analysis is complicated [20]. The difficulty rises even further on cases where the samples exhibit translucency or even transparency. In such cases, although there is usually a specific colour hue that distinguishes the quality and, in some cases, the 'freshness' of the product, the problem gets more complicated. In this work we present a workflow that is applicable to the colour sorting of translucent samples and provide a practical implementation and evaluation example that has been based on sorting the world-known mastiha of Chios.

2. Automated Colour Sorting of Translucent Samples

In this section we present a workflow that is based on computer vision techniques to detect and sort translucent samples with distinctive hues according to their hue and size. The general sorting scenario within the proposed setup includes the following assumptions:

1. clear and uniformly-coloured samples have a higher level of purity
2. size is an important factor and should be used to distinguish the samples
3. colour hue is an important factor in the sorting process but we will not deal with it in this version of the method, which will focus on translucent-white samples

Within the proposed workflow, there is a *specific setup* that guarantees the best possible detection decisions. The main issue in the specific challenge is to tackle with the translucency of the samples. The way that has been selected was to *diminish the translucency without affecting the colour hues and the features that would distinguish impurities*. In addition, an overall *dark environment* would guarantee a clear distinction between the samples and the background. Taking these into account, in the proposed prototype setup the samples are passing one-after-the-other on a conveyor belt through a 'black box' (any kind of black painted enclosing). In this box the samples are lit using white light, while a camera mounted vertically on top of the samples captures realtime frames (images) of each (at least one or possibly more) of the samples as they enter the camera's field of view. Fig. 1 shows a representation of the proposed prototype setup. In this representation a brighter rectangle on the belt just below the camera represents the frame that is being captured.

The captured frames are processed using a specifically designed algorithm that achieves high accuracy in detecting clear samples and sorting by size. Specifically the workflow is as follows:

1. *Dark-pixel rejection*: The captured RGB image is thresholded so that very dark pixels are set to black in order to discard noisy pixels in dark areas (expected to be present due to the typical low-light sensitivity of image sensors). In principle, due to the setup, each image consists of a black background and one or more translucent samples in bright clear hues, including variations in hues and brightness due to impurities.

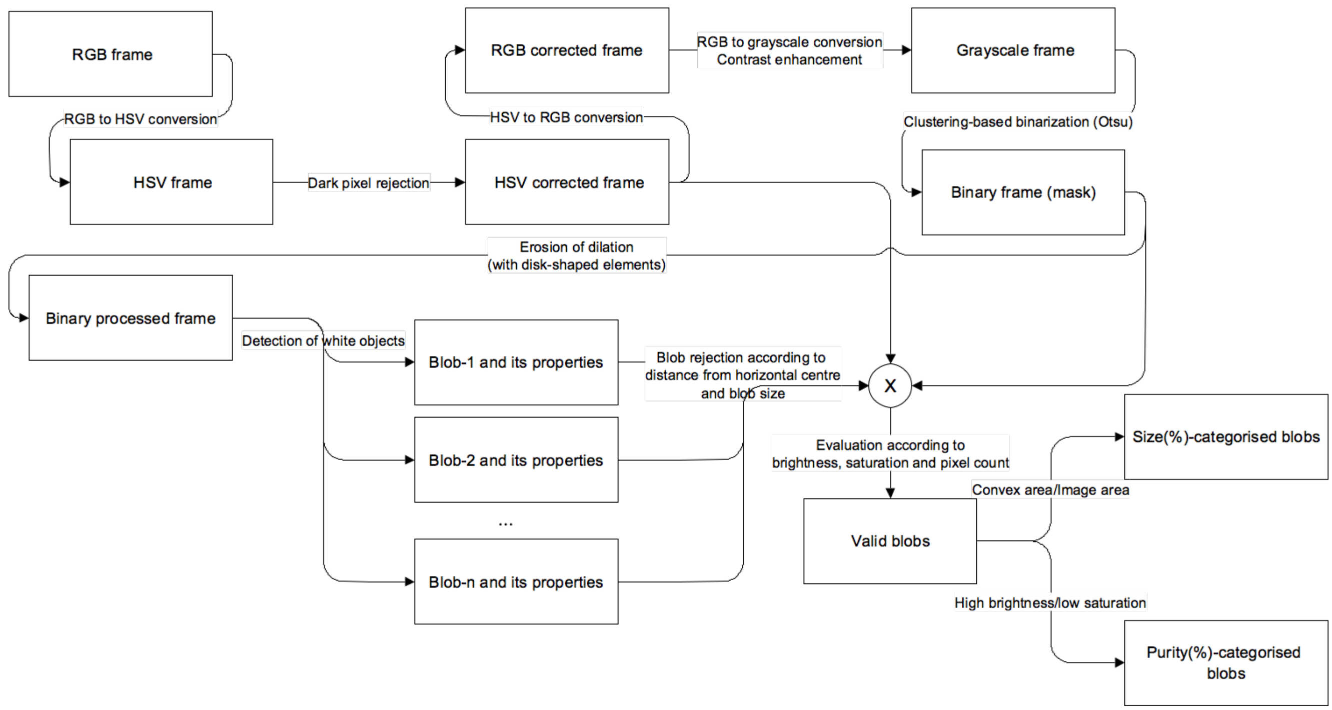

Figure 2: Object-based flowchart of the proposed algorithm

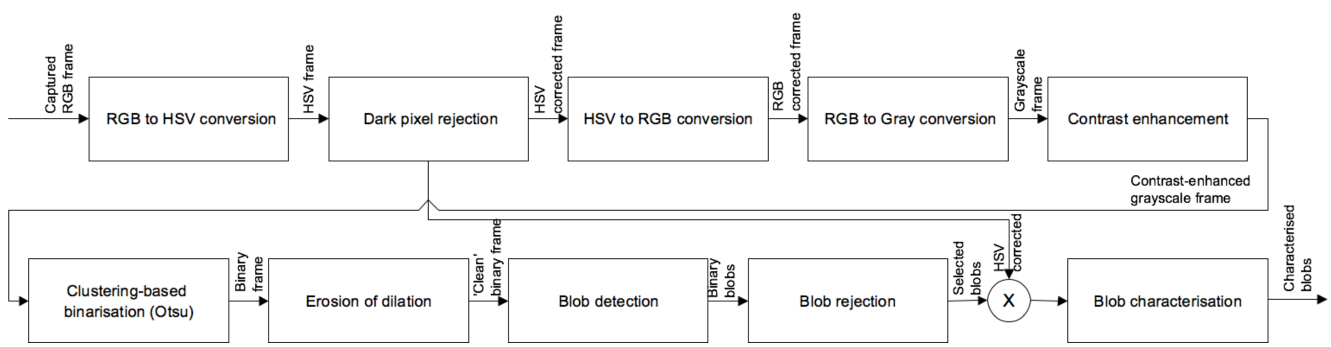

Figure 3: Process-based flowchart of the proposed algorithm

2. *Conversion to grayscale*: The thresholded RGB image is converted to grayscale and its contrast is enhanced to further distinguish the objects from the background.

3. *Conversion to binary*: The grayscale image is converted to binary using clustering-based image thresholding (Otsu's method)[21] in order to acquire a binary mask pinpointing the location of the objects of interest.

4. *Morphological processing*: The binary image undergoes a series of morphological operations that eliminate noise and small objects, connect closely-located objects and finally detect the translucent 'blobs' [22, 23].

5. *Image analysis*: The translucent blobs are analysed and specific measurements are taken, including *bounding boxes, convex hulls, convex areas and centroids.*

6. *Decision making*: The algorithm at the final steps applies some heuristics (thresholds in relative blob size, saturation and brightness of blob pixels) to distinguish the blobs and provide the final sorting decision that includes size and purity. It should be noted that these heuristics can adapt the decision making process to the specific samples and the sorting policy to be applied.

In Fig. 2 we depict the proposed workflow, providing an overview of the 6 processing steps from an object-based perspective. Similarly, in Fig. 3 we show a process-based and more detailed representation of the proposed workflow. As shown, most computations take place in the binary image domain and the overall process is extremely fast even though it includes a number of processes and conversions. In order to test and evaluate the efficiency of the proposed method (the prototype setup and the algorithm) the prototype has been used in a real-world problem, the colour sorting of the mastiha of Chios, a very typical translucent product, a resin with specific colour hues, impurities and size ranges. In the following section we present the challenge and the results of colour sorting produced by the proposed method.

3. The case of the Chios Mastiha

Mastiha is a natural aromatic resin extracted from the mastic tree (Pistacia lentiscus var. Chia), which grows on the island of Chios, Greece (Fig. 4) that is used in food, medicine and the industry. Mastiha is grown and traditionally produced in the southern part of the island of Chios, in particular 24 mastiha producing villages. In these villages about 1800 mastiha producers produce a total of some 1.35 million mastic trees with an annual output that amounts to about 150 tonnes. About 1.1 million trees are being cultivated annually while the rest remain "resting" (for the next year). Cultivation is on a family basis, involving most of the residents of the villages, regardless of gender and age. The collection of mastiha is being done in a traditional way. Workers tear the tree trunk at certain points. The gum begins to flow and in about 15 days is stabilised and is ready for collection. Gathering begins with the larger pieces. Washing of the gum follows, then spreading to drying in an airy indoor space and storage in wooden boxes in a cool place. Small groups, often elderly women, with clean it carefully by hand (Fig. 4). Then the entire production is delivered to the Chios Mastiha Growers Association that processes it, sorts it according to size and quality for various products and promotes it for domestic and international markets [24–26].

Figure 4: Mastiha drops from a mastic tree (left), a collected mastiha (middle), sorting practice(right)

Chios Mastiha Growers Association is currently using an automated sorting system that achieves the separation of mastiha based on purity, but the production is low, inaccurate and the cost that burdens producers is high. In particular, producers are asked to pass their 'non-pure' production through the Associations sorting system, with a cost that increases with the volume of the production that has to be checked. The system is based on a simple detector that integrates the light reflected from the whole sample surface (something like one pixel per sample). Detection is manually controlled (calibrated) according to the expected system response (can be manually set to accept false positive or reject false negative with varying rates). The system operates at low speed. If producers had access to a low-cost high-speed quality control system that would achieve sorting of production by size and purity, then the final sorting costs paid to the Association could be significantly reduced.

To tackle with this real problem, we have applied the proposed method in numerous mastiha samples. Fig. 5 shows the outcome of the basic steps of the algorithm on two mastiha samples with impurities in different proportions. As shown, the upper sample is characterised as 79.7% pure and its convex hull is displayed in blue to distinguish it from the lower sample with a much lower purity of 44% that is displayed in red. In addition, the line-width of the curve of the convex hull is in accordance with the sample area that distinguishes samples by size. Similarly, Fig. 6 shows two samples that have been characterised as pure (purities of 99.7% and 100%) and displayed in green convex boundaries. Again, the curve width corresponds to the blob area that characterises the size. It should be noted that those overlaid indications are just for the real-time presentation system for an overview of the system's response.

It should be noted that all detection conclusions are being made according to the relative (%) measures of size and purity so that the heuristics can be easily altered to adapt to any visual detection system (any camera resolution and any distance from the subjects) along with any set of rules (heuristics for the size and purity) that will use this

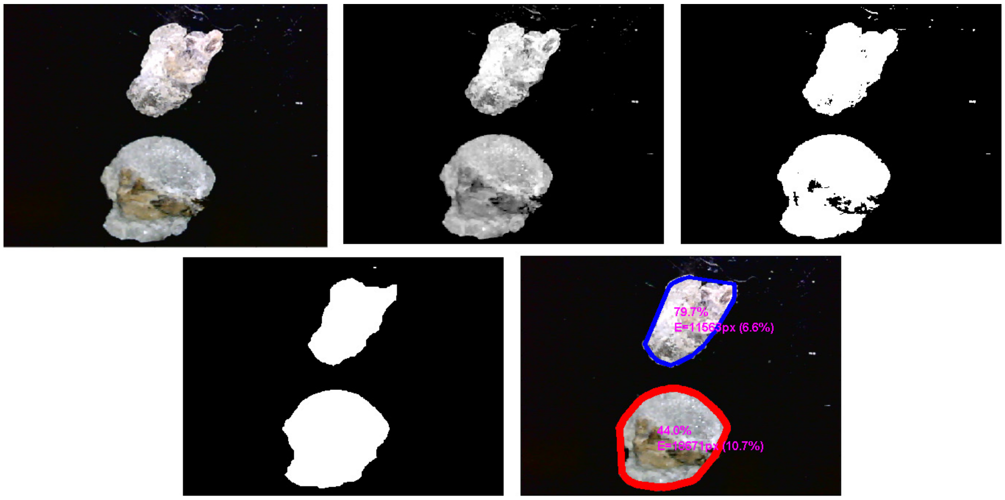

Figure 5: Representation of the basic vision-based mastiha sorting steps using actual images

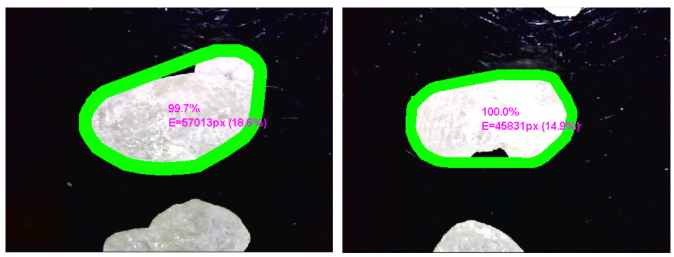

Figure 6: Mastiha samples that successfully pass the quality tests

algorithm. The current version of the algorithm supports the adjustment of the heuristics for purity to any three thresholds that will apply to high, medium and low purity samples with a 'strictness' that is mainly according to the policy regarding the false negatives (i.e. how to preserve as much pure samples as possible).

4. Results and discussion

The algorithm has been extensively tested in the Chios mastiha case study, using numerous samples of various sizes and purity levels and resulted in nearly 100% sorting accuracy (expressed by the true positive and true negative outcomes and compared with a human observer in ideal sorting conditions). It should be noted that the 'accuracy' term here is somehow relative to the expected sorting outcome. In technical terms, whatever the required accuracy, it is closely related to the lighting conditions and the overall setup and is the main factor that could cause the introduction of mismatching issues in the form of false negative and false positive detection. In addition, as will be later pointed out, the quality of the images acquired by the camera (and as of this, the selection of the camera) plays another important role in the system.

In overall, the experiments have shown that fairly simple computer vision practices are able to be used for the development of an efficient algorithm for colour sorting of translucent product samples (such as the Chios mastiha) using very low cost equipment. The experimental setup used for the evaluation of the algorithm that was based on a very low-cost camera with low frame-rate of about 5fps, achieved a realtime detection speed for a product supply of about 3 samples per seconds, definitely a relatively high speed in comparison to manual sorting. Although the detection speed is higher than manual sorting, it can be still considered slow, but this is only due to the imposed camera motion blur (due to the low frame-rate of the camera). Higher speed cameras have been tested and the algorithm was proven to work efficiently providing higher detection rate without compromising accuracy. Fig. 7 shows some selected results of detection attained by the algorithm for the case of the Chios mastiha. The results include various sample sizes and purity degrees.

Another important characteristic that has not been taken into account in the algorithm at its present version is the possible distinctive hue that the samples may exhibit, which in most cases, in translucent samples, corresponds to the 'age' of the sample (the time that passed since the sample was collected from nature). This is definitely true

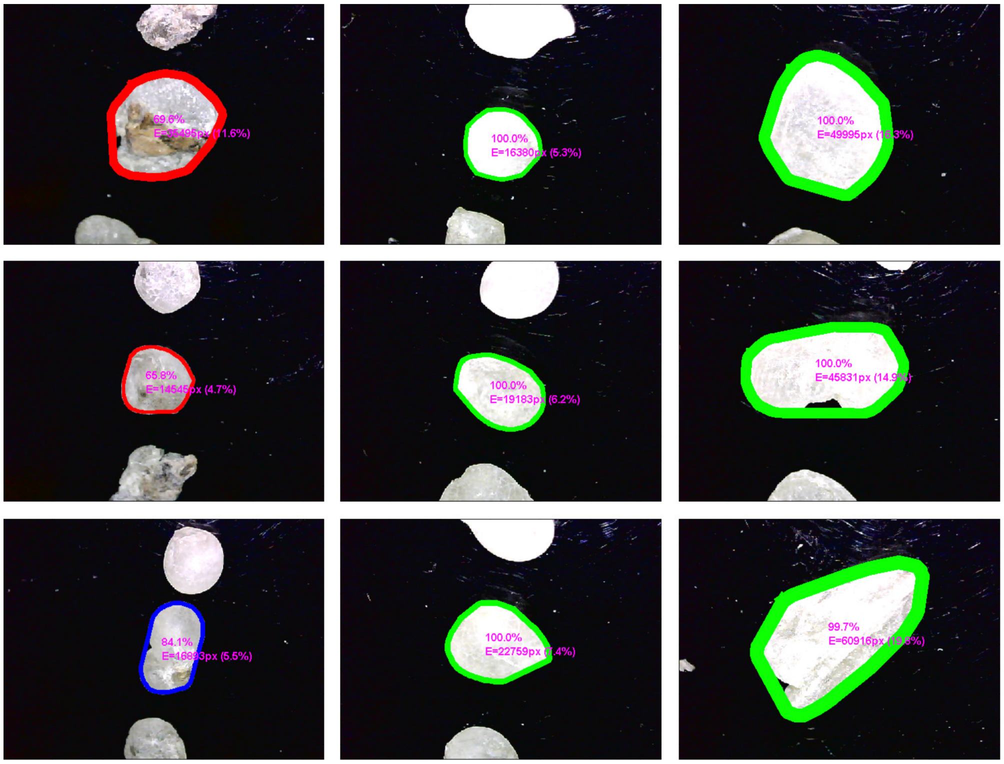

Figure 7: Detection examples: left column shows impure samples of various degrees of impurity and size, middle and right columns show small and large samples of high purity respectively

for the case study, where 'freshly' collected mastiha drops have a white and clear appearance, while older drops become more and more yellow as time passes. This may have an impact in the apparent quality and should be considered for even more sorting possibilities. Further developments of the presented algorithm will include the detection of the specific hues that are crucial to determine the time since the samples were collected and provide additional sorting possibilities. In addition, the imaging system discussed in this paper can be easily adapted to a complete sorting system, including the mechatronics, to provide an integrated solution to the automated colour sorting of translucent product samples. Such a prototype system is another of our future directions.

5. Conclusion

Translucent samples constitute a special case of samples that have to be tackled somehow differently in colour sorting practices due to their transparency. In this paper we presented a complete computer-vision-based method to automate colour sorting of translucent samples that relies on a series of well-established vision techniques and a carefully planned setup that is able to be integrated in a future colour sorting mechatronic system directly applicable to industrial production. We used the mastiha of Chios as the case study, since it is a world-renowned product and the mastiha growers are in need of such a system (so there is a realistic applicability for the proposed approach). The algorithm has been tested using numerous mastiha samples of various sizes and purity levels and resulted in nearly 100% sorting accuracy, but this can be fine-tuned to match any selected policy against false positive or false negative outcomes. Next steps of the developments of this method include the detection of specific distinguishable hues that will enable the automatic determination of the time since collection, along with integration into a complete mechatronic quality control prototype.

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