Efficient Colour Sorting of Chios Mastiha

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***Abstract*—Mastiha is the natural aromatic resin extracted from the mastic tree, which grows on the island of Chios, Greece. It is grown traditionally in 24 mastiha villages producing about 150 tonnes annually. Producers collect and sort their mastiha production by hand. This work aims at providing a feasible and implementable solution of an optical sorting algorithm to Chios mastiha producers. The method is based on visual detection and sorting of mastiha samples in the visible spectrum within a controlled setup following a low-cost approach and was found to achieve sorting results of very high accuracy with even more categorisation possibilities.**

I. Introduction

Applications of computer vision in industry are increasing considerably in the recent years due to fact that both imaging equipment and sophisticated vision algorithms can be effectively introduced in a production line and are able to increase the efficiency of automated processes in various circumstances. These applications include crops monitoring, automated guidance, non-destructive inspection, quality control and sorting, mechatronics and robotics, and more. This wide range is due to the nature of computer vision to provide image-based decision making procedures in real-time applications, and, in some cases, to exploit information otherwise not available to humans (such as in multispectral imaging).

One area where the use of this technology has spread rapidly is the inspection of food products and in particular in the automatic inspection of vegetables and fruits. This area of applications has been active for many decades and has provided the industry with numerous successful systems that boosted the production in large scales [1]–[19]. 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. Among these properties, maturity, size, weight, shape, colour, presence of dirt and diseases, presence or absence of stem, presence of seeds, sugar content, can be identified as predominant [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 have traditionally been evaluated by a visual inspection performed by qualified personnel, but today have been replaced (to an extent) by commercial automatic inspection systems based on computer vision and image analysis [9]. A relatively high risk of human error lies upon manual sorting processes, as decisions can be affected by psychological factors such as fatigue or acquired habits. It should be noted that automated inspection of agricultural products exhibits some peculiarities due to the biological nature of the inspected products, 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; not to mention that such products naturally evolve even after harvesting, changing 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. The nature and parameters of the problem show that the development of algorithms capable of extracting quality decisions from image analysis is complicated [20].

Mastiha is the natural aromatic resin extracted from the mastic tree (Pistacia lentiscus var. Chia), which grows on the island of Chios, Greece (Fig. 1). Mastiha 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. 2). 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 [21]–[23].

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 grows with the volume of the production that has to be checked. The system

(a) Mastiha drops (b) Collected mastiha sample

Fig. 1: Mastiha drops from a mastic tree (1a) and a collected mastiha (1b)

Fig. 2: Mastiha sorting practice

is based on a simple detector that integrates the light reflected from the whole sample surface. Detection is manually controlled (calibrated) according to the expected system response (can accept false positive or reject false negative). The system operates at low speed (but still higher than manual sorting). 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.

Tackling with this issue, this work aims at providing a feasible and implementable solution of an optical sorting algorithm for Chios mastiha. The method is based on visual detection and sorting of mastiha samples in the visible spectrum within a controlled setup. The following sections present the proposed setup and workflow along with the detection results and conclusions.

II. Automated Colour Sorting

Since manual sorting of Chios mastiha is based on visual detection, a computer vision technique may be devised to replicate the manual process using sophisticated algorithms or specific workflows. This paper proposes a workflow that is based on computer vision to detect and sort mastiha drops according to their colour hue and size. In this workflow, the samples are passing through a black box that is lit using white LED light of controlled brightness, while a camera mounted vertically on top of the samples captures realtime images of each of the samples as they enter the camera's field of view. The captured images are processed one-by-one 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. In principle, each image consists of a black background and one or more mastiha samples in bright white or yellowish hues (including variations in hues and brightness due to impurities)
2) *Conversion to grayscale*: The thresholded RGB image is converted to grayscale and its contrast is enhanced
3) *Conversion to binary*: The grayscale image is converted to binary using clustering-based image thresholding (Otsu's method) [24]
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 mastiha 'blobs' [25], [26]
5) *Image analysis*: The mastiha 'blobs' are analysed and specific measurements are taken, including: *Bounding Box, Convex Hull, Convex Area, Centroid*
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

Fig. 3 graphically depicts the proposed workflow providing a more detailed view of the 6 steps described in the previous paragraphs from an object-based perspective. Similarly, Fig. 4 is a process-based graphical 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.

Fig. 5 shows the outcome of the basic steps of the algorithm on two samples with impurities in different proportions. As shown, the sample above is characterised as 79.7% pure and its convex hull is displayed in blue to distinguish it from the other sample with a much lower purity of 44% that is displayed in red. In addition, the 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.

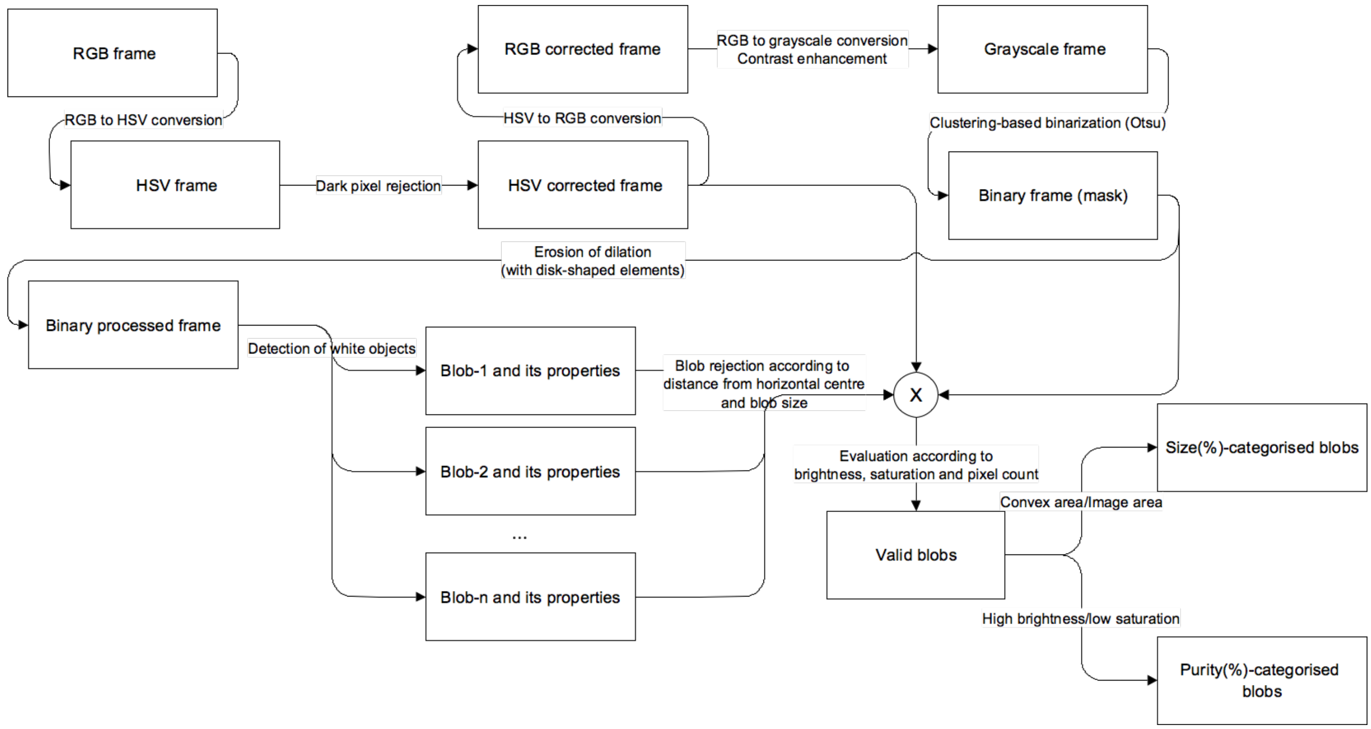

Fig. 3: Object-based flowgram of the proposed workflow

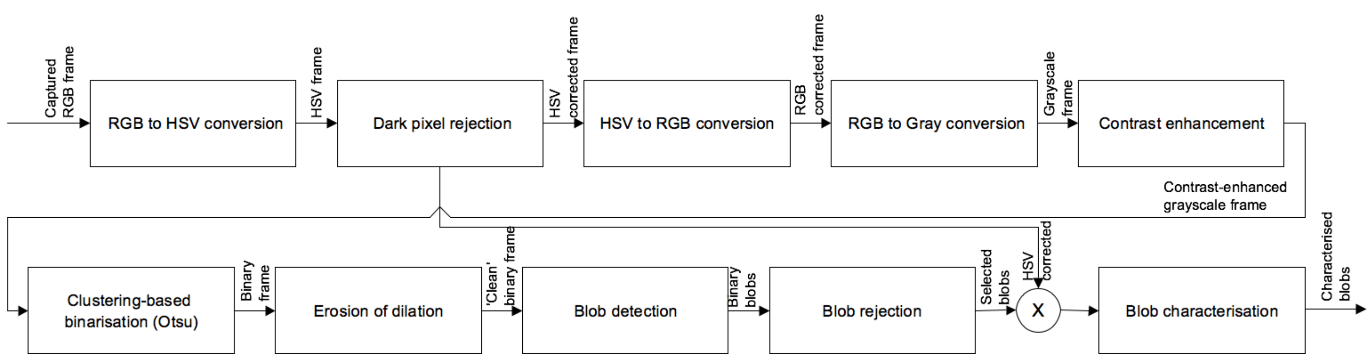

Fig. 4: Process-based flowgram of the proposed workflow

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 algorithm. At the current state of the algorithm the heuristics for purity can be adjusted 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).

III. Results and Discussion

The algorithm has been extensively tested using numerous samples of various sizes and purity levels and resulted in nearly 100% sorting accuracy (as expressed by the true positive and true negative outcomes and as 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.

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 the Chios mastiha samples using low cost equipment. The current experimental setup (using 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 (which is a relatively high speed in comparison to manual sorting). Although the

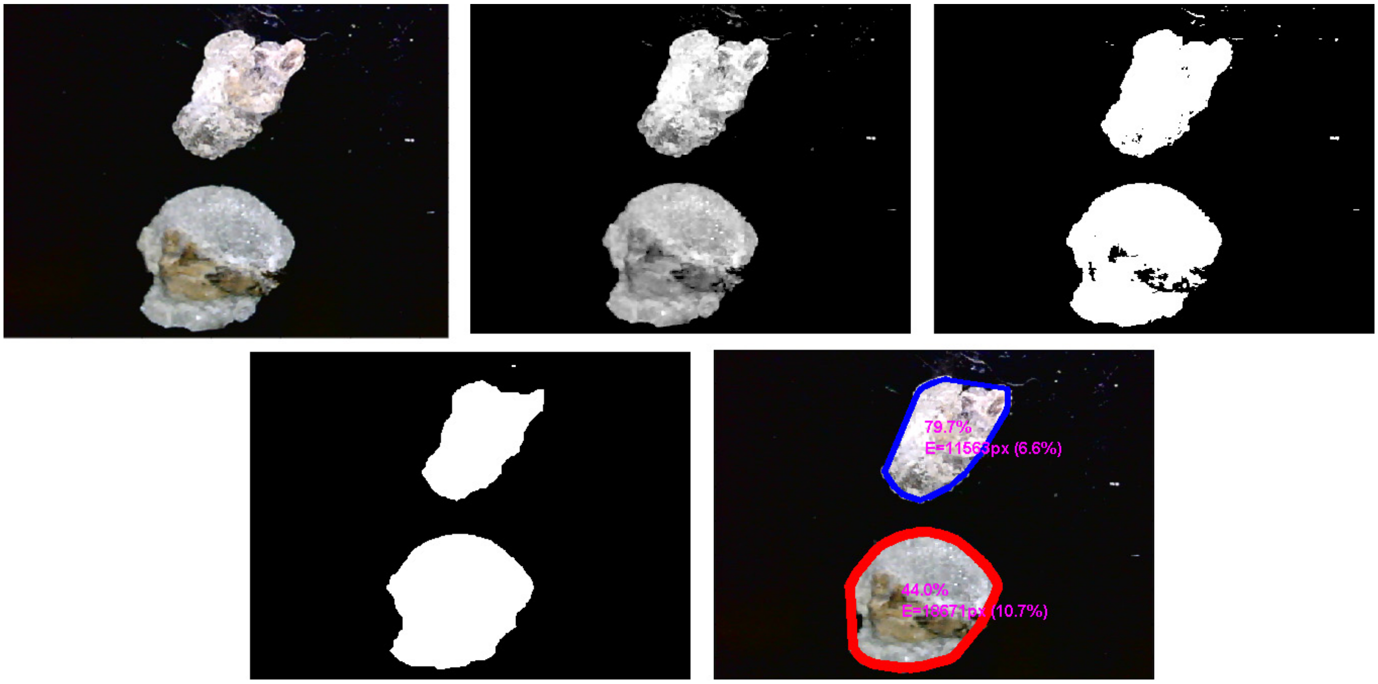

Fig. 5: Representation of the basic vision-based mastiha sorting steps using actual images

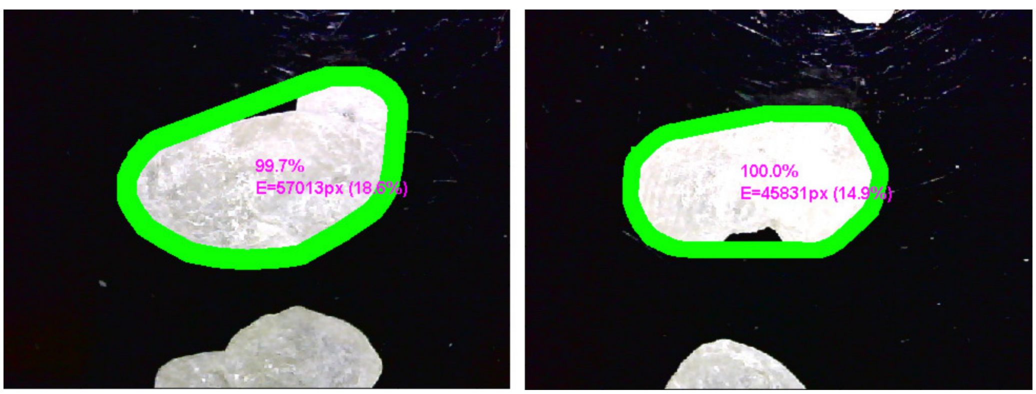

Fig. 6: Mastiha samples that successfully pass the quality tests

detection speed is higher than manual sorting, can be still considered a slow speed, but this is only due to the specific camera motion blur. 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. The results include various sample sizes and purity degrees.

Another important characteristic that has not been taken into account in the presented algorithm is the mastiha samples' hue, that is, the 'yellowness' of the samples, which corresponds to the 'age' of the sample (the time that passed since the sample was collected from the tree). 'Freshly' collected 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 algorithms will include the detection of the mastiha hues (shades of yellow) to determine the time since the mastiha was collected and provide more sorting possibilities.

In addition, the imaging system discussed in this paper can be easily adapted to an overall sorting system to provide an integrated solution to the automated colour sorting of Chios mastiha samples. Another of our future directions is towards developing such a prototype that will be able to provide the overall quality control line.

IV. Conclusion

Mastiha is a significant product that contributes to the local economy of the island of Chios, Greece. To this day, mastiha producers have to go through a manual sorting process that costs many people a lot of time. At a final step they have to pass their production through their association's sorting system

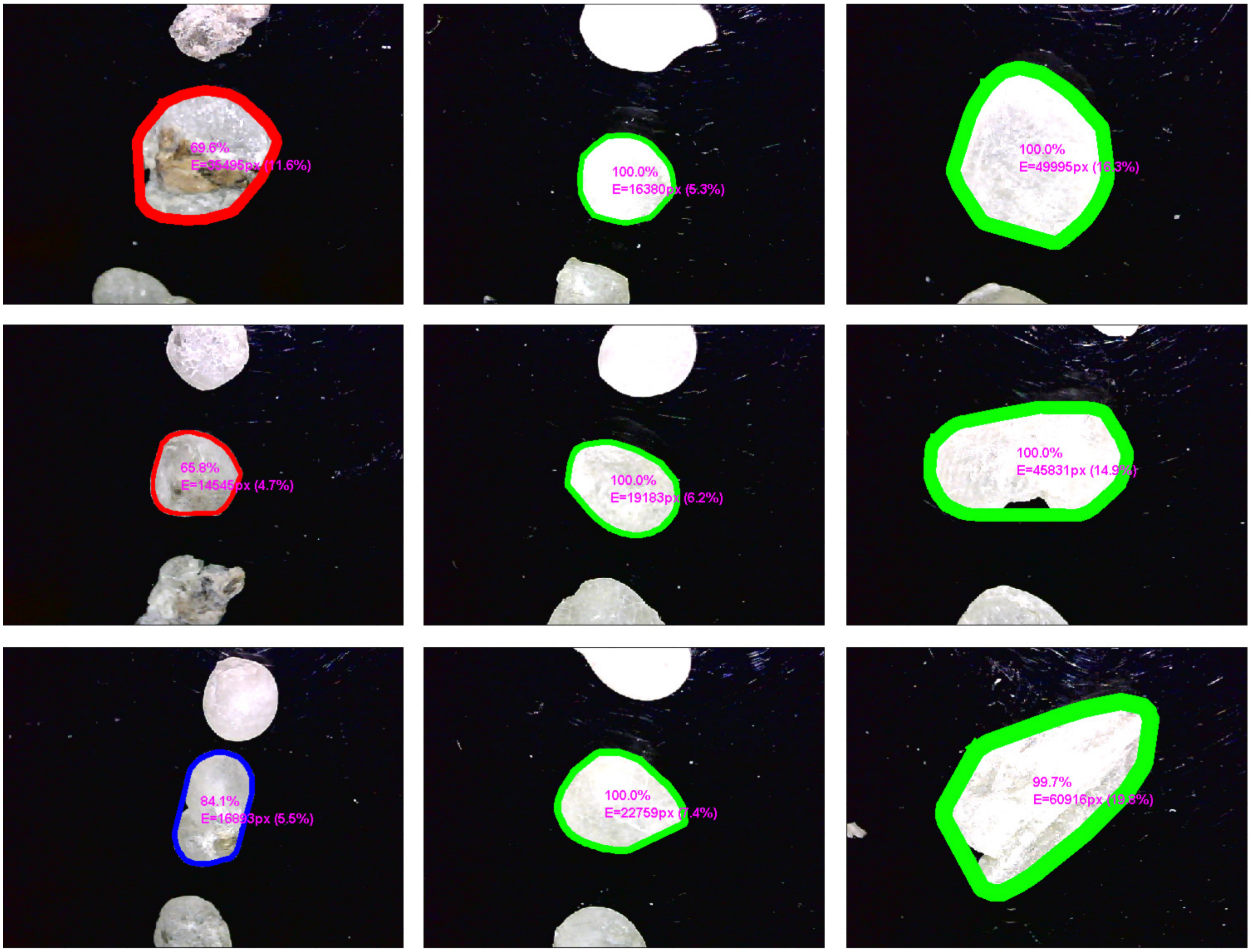

Fig. 7: Detection examples: left column shows impure samples of various degrees of impurity and size, middle and right columns show small and large samples of high purity respectively

that imposes additional costs. This work aimed at developing an optical sorting algorithm to Chios mastiha producers. The method was based on visual detection and sorting of mastiha samples in the visible spectrum using low-cost components and was found to achieve sorting results of very high accuracy providing even more categorisation possibilities than what is available today through the manual sorting employed.

The algorithm has been tested using numerous samples of various sizes and purity levels and resulted in nearly 100% sorting accuracy (as expressed by true positive and true negative outcomes and as expected by a human observer under ideal conditions), but this can be fine-tuned to match any selected policy against false positive or false negative outcomes.

Next steps in the development of this method will include the detection of the mastiha hues (shades of yellow) that will enable the system to automatically determine the time since the mastiha was collected, along with integration efforts to produce an overall quality control prototype.

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