Machine Vision Algorithm for Determining the Orientation of Nearly Flip-invariant Parts in Vibratory Feeding Applications – Low-cost Implementation and Experimental Validation

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***Abstract*—The paper presents a machine vision algorithm for determining the orientation of nearly flip-invariant parts in vibratory feeding applications. The algorithm is designed and implemented within a low-cost hardware configuration. Preliminary experimental results show excellent performance with perfect orientation classification in almost "real-world" operating conditions.**

***Index Terms*—Image processing for machine vision, low-cost machine vision system, vibratory feeding application**

I. INTRODUCTION

Machine vision is a powerful tool for automating modern production processes, bringing increased efficiency and productivity when properly used. With the ever more common availability of high-performance GPU-enabled computing hardware and the development of machine learning techniques such as convolutional artificial neural networks, a novel, data-driven approach towards machine vision gains momentum bringing the promises of enhancing classical methods and the possibilities to tackle a whole new set of machine vision tasks. A good overview of the state-of-the art and future directions in the development of the field can be found in [1]. Application cases using "classical" approach techniques can also be found in [2-6]. Embedded low-cost implementations of machine vision systems can be found in [7-10].

In this paper, a machine vision algorithm and hardware setup is proposed for classifying parts characterized by almost complete flip-invariance according to orientation in two classes. The overall algorithm is designed with the idea of tackling the effects of the undesirable operating conditions encountered within vibratory feeding systems, i.e.:

- moving objects to be subjected to visual analysis, given that no or minimal impact on the feeding process is desirable;
- generally, varying speed of movement, accompanied with vibrations impacting captured image quality.

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Moreover, as the machine vision system usually comes as an adder to an existing feeding system, constraints regarding the overall environmental and lighting structuring are in place, that is, camera and/or light source placement and overall arrangement is subject to limitations. On the other hand, integrating machine vision within vibratory feeding systems could unleash big potential for simplifying complex part sorting, separating and organizing tasks by adding vision guided mechanically less complex active component in the system to complement the mechanically passive (static) part handling inherent to vibratory feeders.

The particular task considered in the paper is related to identifying the orientation of a plastic, black-colored bushing as it sits in the exit section of a vibratory feeder cup. The part is shown in Fig. 1.

Fig. 1. Plastic bushing with almost complete flip-invariance

The hardware and software components of the proposed system are described in Section II. The classification algorithm is discussed in Section III with first experimental results and analysis, given in Section IV.

II. HARDWARE/SOFTWARE SYSTEM CONFIGURATION

Jetson Nano V2 is used as computing platform with customized Ubuntu Linux OS and JetPack 4.4 NVidia SDK including OpenCV-V2 library set. The camera used in the setup is built around the Sony IMX219, 8MP sensor and has

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an angle of view of 77°. The classification algorithm is implemented as Python 3 script.

The positioning of the plastic bushing in the output section of the feeder is depicted in the left side of Fig. 2, along with the lighting and camera enclosure sitting above. The lighting system, designed specifically for the particular application and the positioning of the camera within are shown on the right. Within the lighting setup design process, it was found that diffused light source with stronger intensity helps achieving favorable conditions for image segmentation in addition to the insensitivity with respect to ambient lighting. The output section was painted white to achieve better contrast, thus helping the part segmentation.

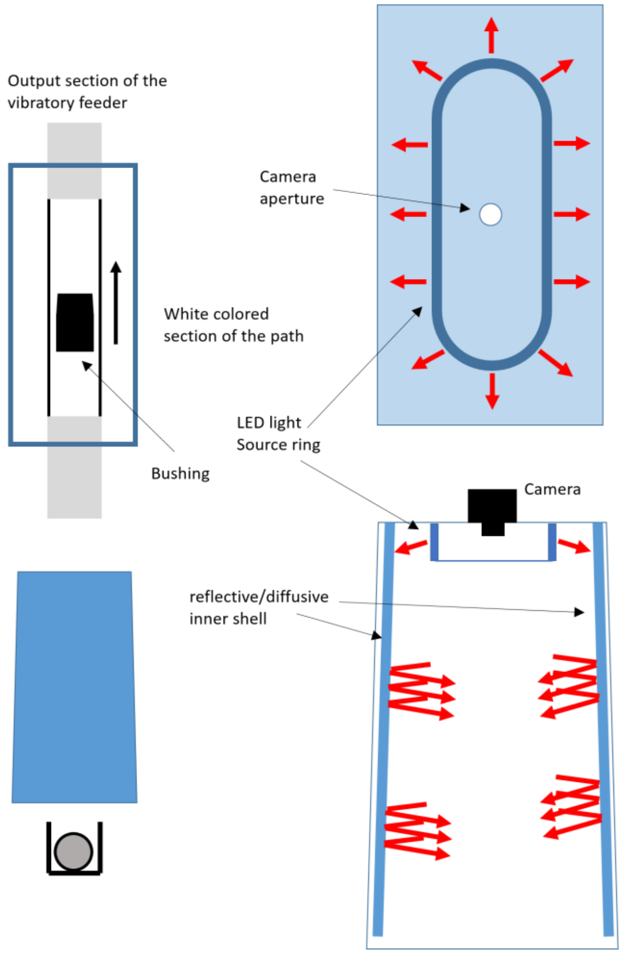


Fig. 2. Camera and lighting setup

III. Algorithm Description

The algorithm flow chart is presented in Fig. 3. The passage of a single part under camera's view area is required for analysis. 200 frames were allowed in the experiments for each passage. Details regarding the most important steps of the algorithm are given in the following:

1) The part of the image, subject to analysis is of size 300x600. Camera resolution is set 800x600 with a framerate of 120 fps. The average processed frame rate was around 15 (p)fps, with average values per classification in the range 15.65 - 13.77.

2) Conversion was done using the OpenCV-V2 library function, according to the following formula:

$$Y = 0.299R + 0.587G + 0.114B \qquad (1)$$

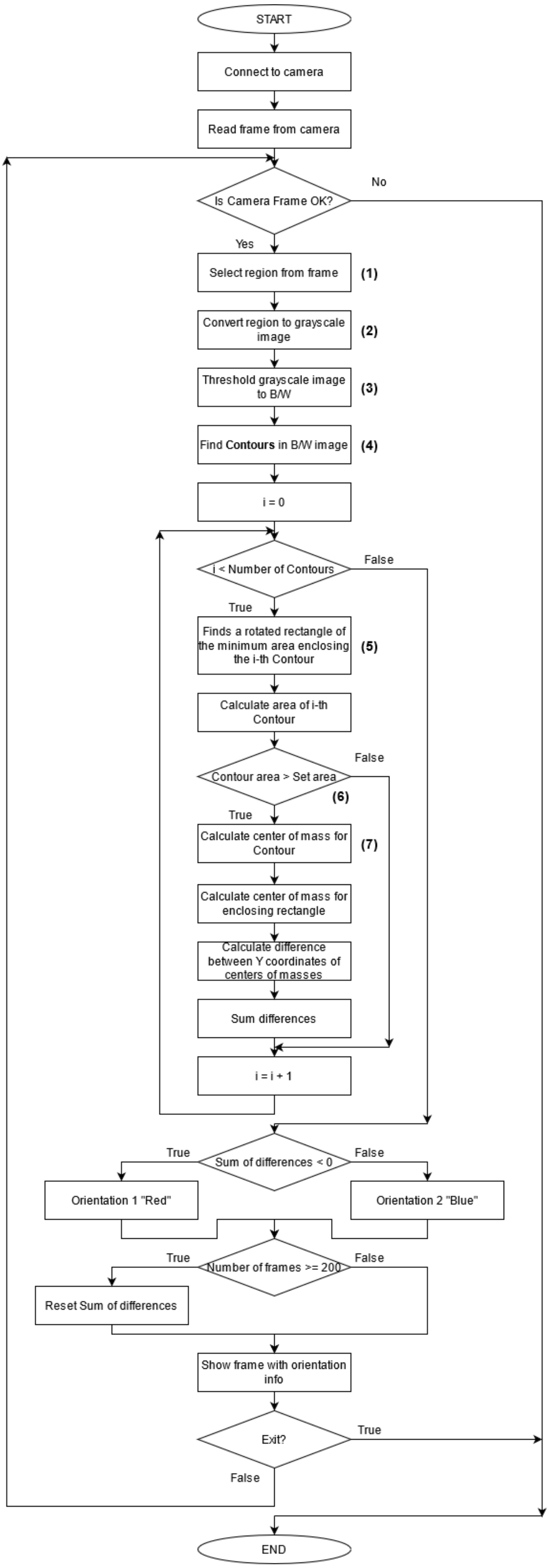


Fig. 3. Classification algorithm flow chart

3) The threshold value for the experiments is set to 200 (of 255). This value was found experimentally. It was also observed that classification performance was not affected within and a “healthy” margin of around 20 which simplifies system’s tuning.

4) OpenCV-V2 library function is used;

5) OpenCV-V2 library function is used;

6) This parameter was tuned experimentally. Its optimal value is determined by the size of the segmented part in pixels within the captured and subjected to processing frame.

7) OpenCV-V2 library function is used;

Details about steps 4), 5) and 7) can be found in [11].

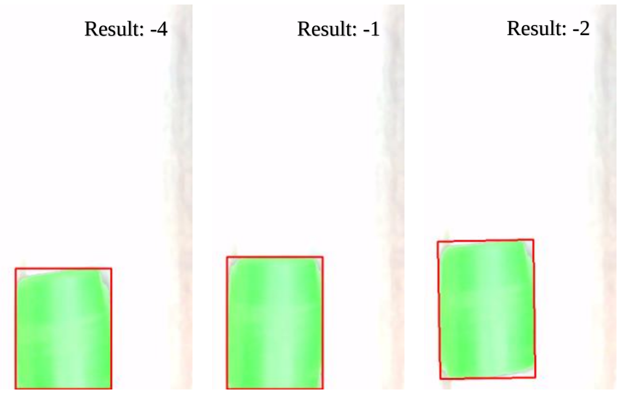
IV. Experimental Results and Conclusion

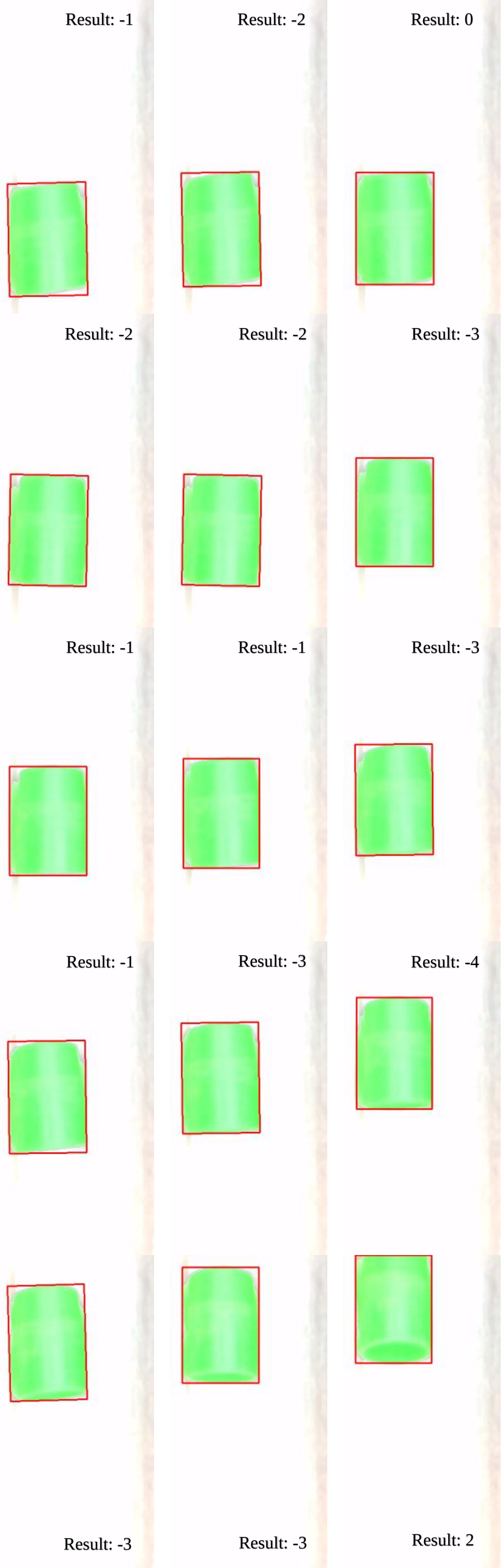
Two sets of experiments were conducted, each with 8 passages of the plastic bushing flipped in the same direction. A single isolated bushing is driven by the vibratory feeder through its output section under the camera/lighting box of the vision system. Several frames were captured and processed according to the proposed algorithm. Results are summarized in the following tables.

Pass	Result	Processed frames	Frames with wrong classification	Frames with neutral result
1	-34	18	1	1
2	-38	19	1	1
3	-59	27	1	2
4	-55	26	1	0
5	-19	17	2	7
6	-33	16	1	1
7	-4	16	6	4
8	-40	17	0	3

Pass	Result	Processed frames	Frames with wrong classification	Frames with neutral result
1	32	22	2	4
2	21	18	2	5
3	29	20	4	3
4	18	18	1	4
5	41	30	2	3
6	21	20	1	3
7	23	24	4	4
8	21	18	4	1

As can be seen, 100 % success in classification was achieved.





The captured and processed frames, along with the classification result per frame for pass 1 in the case of “negative” orientation are shown in the picture sequence on the previous page. The bushing, segmented by the algorithm (in green), along with the enclosing rectangle (in red) are shown in each frame. It can be seen that in only one case we have wrong decision of +2 and in one other we obtain indeterminate output (result equal to 0), both being compensated in the aggregate result. The sum of all “per frame” results is equal to -34, as shown in the first table.

Further testing confirmed 100% success rate, accompanied by an insensitivity with respect to ambient lighting and camera mounting orientation tolerances. It was found in experiments that system’s performance was mostly affected by camera/lighting box mounting height, which had to be set properly in order to have good lighting conditions, leading to reduced glare and ultimately successful classifications. Mounting height also affects the optimal value in step (6) of the algorithm. Increasing height was found to be favorable for achieving better results, though it can be argued that this would also lead to increasing the influence of ambient lighting.

In conclusion, an original algorithm for determining the orientation of the nearly flip-invariant parts, driven by vibratory feeders is proposed in the paper. The algorithm relies on processing multiple frames for a given classification in order to compensate for both low sensitivity of classified parts’ geometric properties with respect to change in orientation and the presence of vibrations, promoting lower quality, e.g. blurring in captured frames. The proposed algorithm is implemented on low-cost computing platform and is easily tuned. The chosen platform gives the possibility of implementing data-driven approaches to the solution of similar machine vision problems, such as implementing and tuning convolutional artificial neural networks, which will be the next direction of research planned by the authors in the overall goal to achieve easier to set up and operate machine vision systems.

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