Implementation of particle image velocimetry for silo discharge and food industry seeds

Romina Molina[1,2,4], Valeria Gonzalez[2], Jesica Benito[3], Stefano Marsi[1], Giovanni Ramponi[1], and Ricardo Petrino[2]

[1] Università degli Studi di Trieste — IPL, Dipartimento di Ingegneria e Architettura
Piazzale Europa, 1, 34127 Trieste TS, Italy
[2] National University of San Luis — LEIS, Department of Electronic
[3] National University of San Luis — INFAP, CONICET, Department of Physics
Av. Ejército de los Andes 950, D5700 BPB, San Luis, Argentina
[4] The Abdus Salam International Centre for Theoretical Physics — MLAB
Strada Costiera, 11, 34151, Trieste TS, Italy
`{rominasoledad.molina}@phd.units.it`

Abstract. *This work focuses on determining the velocity profile of a granular flow at the outlet of a silo, using artificial vision techniques. The developed algorithm performs a frame enhancement through neural networks and the particle image velocimetry detects seed motion in the hopper. We process 50, 100, 150 and 200 frames of a video discharge for three different grains using: CPU and PYNQ-Z1 implementations with a simple image processing at pre-processing level, and CPU implementation using neural network. Execution times are measured and the differences between the involved technologies are discussed.*

Keywords: PIV, image processing, SoC

1 Introduction

The growth of artificial vision techniques for image processing, recognition and classification permits to expand the expectations of the systems to solve problems that otherwise are much more difficult or impossible in different fields as security, industry, autonomous drive, among others [1–3].

In this work, we present the design of an artificial vision application for the calculation of the velocity field in a granular media at the outlet of a silo. The study of granular flows within silos is a topic of great interest due to its influence on different industrial processes (emptying, mixing, grinding and transfer of material) in industries such as cement, pharmaceutical, food, mining, among others. In food industry, there are countless examples where silos intervene in production processes, presenting problems associated with the geometry and characteristics of the silo and grains [4–6]. When the silos are not designed properly, serious difficulties can arise in the discharge flow, leading to non-homogeneity of mixing or blockages in hoppers.

Therefore, it is highly relevant to know the characteristics of the granular flow. This work focuses on determining the velocity profile at the outlet of a silo using artificial vision techniques: (a) video enhancement (b) image processing in frequency domain using Fast Fourier Transform.

2 Experimental setting under study

The device used in the experiments is shown in Fig. 1 [6]. It consists of a quasi-2D silo, with acrylic walls and mobile rods that allow to vary the silo outlet opening and the angle of inclination of the hopper. Transparent walls allow visualizing the flow during discharge. The granular material used are seeds typically employed in food industry: black sesame, millet and canary seeds (Fig. 1). The shape and color of the seeds present a hard challenge due to the difficulty to identify them during the rapid discharge close to the outlet. Also, in these experiments, the hopper angle is 90° (measured from the vertical), known as a flat silo. Furthermore, the outlet opening is large enough to avoid blockages. This configuration presents a rapid discharge zone in the center of the silo and stagnation zones near the walls.

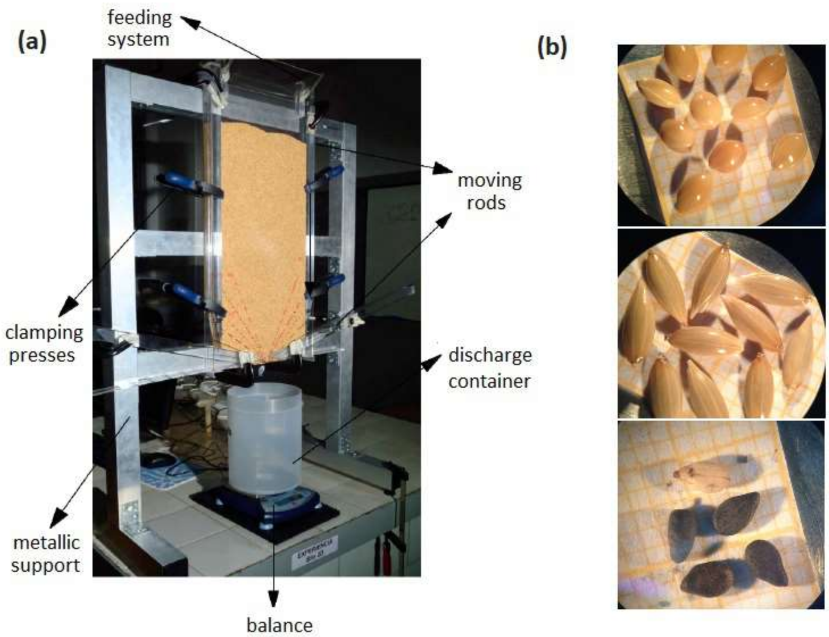

Fig. 1. (a) Experimental device. (b) Grains (from top to bottom): millet, canary seeds and sesame.

Particle image velocimetry (PIV) determines the displacement of particles in a certain flow using two images captured in a known time interval. Thus, it is required a video or image sequence of the silo discharge to be analyzed. In our experiments video is captured with a digital camera IDS UI-3160CP-C-HQ Rev.2.1, with a resolution of 900x400 pixels at 100 fps for millet seed and 940x328 pixels at 142 fps for black sesame. Input frame examples can be see in Fig. 2.

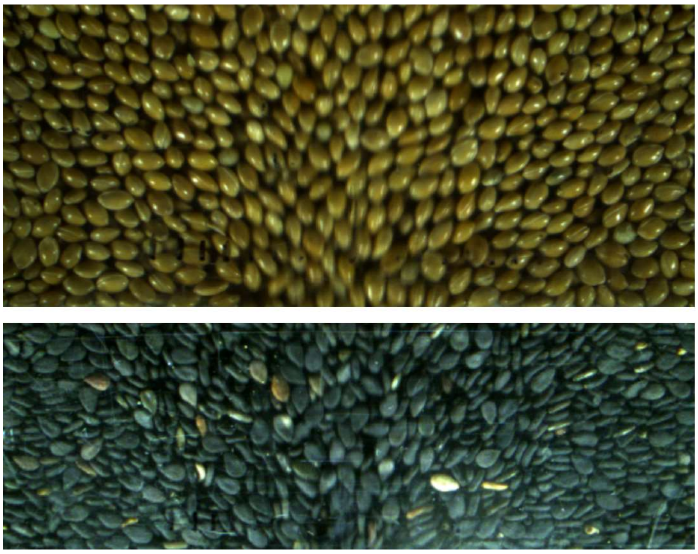

Fig. 2. Input frame - Millet (top) and black sesame (bottom)

Through the PIV processing, it can be determined the displacement (magnitude and direction) of the particles and, therefore, their velocity [7]. To implement this technique, each frame of the video is divided into a certain number of areas distributed over the image (interrogation windows).

3 Particle image velocimetry algorithm: design and implementation

The proposed algorithm employs artificial vision techniques and has three main stages: (1) Frame enhancement, (2) Particle image velocimetry (PIV) algorithm to detect seed motion and (3) Motion vectors debugging.

3.1 Stage 1: Frame enhancement through neural networks

This stage improves the quality and appearance of each frame affected by experimental conditions (such as non-homogeneity in lighting, low brightness, noise, color distortion), to improve the subsequent tasks. We employ two techniques: (a) based on simple image processing, which involves conversion of the input frame to the HSV color space, followed by a per-element bit-wise conjunction with a predefined mask, and (b) based on neural network using WESPE [8] architecture, an image-to-image Generative Adversarial Network-based architecture with openly available models and code. Both techniques were included into the video-processing pipeline in separate experiments.

As regarding neural network implementation, the training was performed using strong supervision, with the DPED dataset introduced in [9], with some modifications in the original architecture: (i) the weights for each loss were modified: w_content (reconstruction): 0.2, w_color (gan color):25, w_texture (gan texture): 3, w_tv (total variation): 1/600 (ii) for the content loss, relu_2_2 layer from VGG19 was used. The training parameters were configured as follows: learning rate: 0.0001, batch size: 32, train iterations: 20000.

It should be observed that implementing a unique pre-processing technique makes the deployment of Stage 1 independent of the input video, i.e. permits to process different types of seeds with the same algorithm, avoiding specific techniques for each seed and generating a robust long-term processing technique. Our experiments put in evidence that, on the contrary, traditional enhancement methods without neural networks needed to be modified and tuned differently for the different cases.

Once the enhancement is performed, each frame is converted to gray scale to be used as input in the next stage. Fig. 3 shows the input frame in gray scale (left) and the output frame of this stage using the neural network (right).

3.2 Stage 2: Particle image velocimetry algorithm

In this stage we determine the displacement of the particles within each interrogation window. An optimal window size has to be used in order to obtain a high accuracy without generating invalid vectors. Here, the image is divided into 18x8 (millet) and 18x6 (sesame) windows.

By decreasing the window size, the number of resulting speed vectors increases and thus it is possible to estimate the direction and speed of the seeds with better accuracy. But this is not always optimal, if the window size is less than the proper size of the seed, it may happen that the real movement of the seeds is not detected, generating invalid displacement vectors. And, if the size of the windows is very large, a loss of information occurs.

Then, we calculate the Fast Fourier Transform (FFT) for each interrogation window and the individual spectres of each subsequent interrogation window are multiplied. Finally, we calculate the Inverse Fourier Transform to obtain the position having the maximum correlation value. This information results in the displacement vector of the grains within that window.

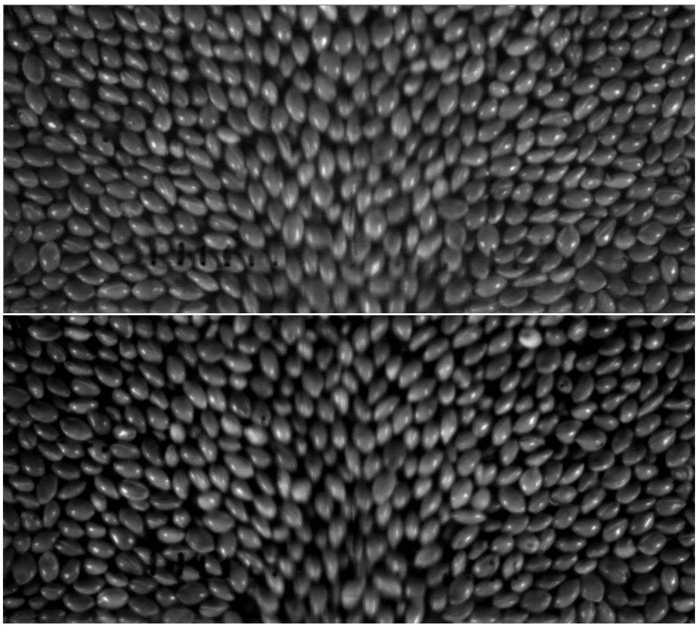

Fig. 3. Input frame in gray scale (top). Output of the pre-processing stage using neural network (bottom)

3.3 Stage 3: Debugging the motion vectors

Incorrect vectors are inevitable in the processing due to: size of the windows, stagnant or almost immobile seeds on the sides of the silo, very fast motion of the seeds between two subsequent frames, among others. With debugging, vectors are subjected to a reduction, validation and replacement. This is done comparing the resulting vectors with those obtained in neighboring windows. If there are inconsistencies the vector is eliminated and replaced by an average obtained from all neighboring windows.

Finally, with the calculated displacement and the time interval between frames, we determine the velocity field along the hopper.

4 Embedded implementation using System on Chip

The implementation of increasingly complex systems is possible due to the development of modern technologies that allow on-chip systems to include the Processing system (PS) and Programmable logic (PL) in a single integrated system. These technologies permit a Hardware/Software (H/S) co-design for a reduction in processing time. In this context, with PYNQ (Python + Zynq) framework [10] we can create applications with SoC and MPSoC devices, using Python through Jupiter Notebook, at PS level and a certain available hardware configurations of the PL, through the so-called overlays.

The main algorithm to implement PIV technique was developed and tested in CPU and, after verifying the correct functionality, it was ported to the System on Chip using Jupyter Notebook in the processing system through Ethernet connection.

The measurements of the execution times is the first step to perform the co-design H/S in future works, to obtain a final embedded implementation for the complete system, looking forward to obtain real time processing in a portable device.

5 Results

Experimental setup: The algorithm was implemented and executed on a CPU Core i7 3.4GHZ 64GB RAM GeForce GTX 1070, using the Python 3.6.7, TensorFlow 1.12 and OpenCV 3.4.1 libraries. For the embedded implementation, PYNQ-Z1 board from Xilinx was used. The input videos were captured with a digital camera IDS UI-3160CP-C-HQ Rev.2.1, with a resolution of 900x400 pixels at 100 fps for millet seed and 940x328 pixels at 142 fps for black sesame.

Fig. 4 (a) and (b) show the results (velocity field) for the millet and sesame seeds. It can be noted that this technique predicts quite well the motion of the grains in the different zones of the hopper. Possible errors can be related to: stagnation zones (grains move very slowly, or short displacement every many frames), or very fast motion (central region with fluctuations of the flow). It is also important to note that results for sesame seeds are very good despite the fact that grains have a very different geometry and color compared to the millet.

Regarding the execution times, the experiments were carried out by processing 50, 100, 150 and 200 frames of the discharge in different technologies and with 3 types of grain as input: CPU implementation, PYNQ-Z1 implementation, both with simple image processing at pre-processing level, and CPU using neural network.

The results are presented in Table 1. As we can observe, the rise in execution time is directly proportional to the increase in processed frames. Also, the differences between the involved technologies are related with the processing system: CPU with i7 and PYNQ-Z1 with dual-core Cortex-A9. Despite run time differences, the algorithm was fully implemented in the embedded system, enabling the next stage of H/S co-design.

The speed of the grains at the final line of the outlet vs. position is shown in Fig. 5. With 200 processed frames, better results are obtained (less fluctuations), even if the execution time is larger than the one obtained with 50 frames. The behavior of the speed observed at the exit of the silo (Fig. 5) is the expected one for a granular discharge [6], this is, the speed in the center of the hopper is higher and, as the grains approach the edges of the outlet opening, it tends to zero. Besides, the curves have the shape of an arc (typical arc formed by the particles in the outlet where they describe a free fall). It also can be observed that black sesame grains present higher velocities than the millet ones. This may be due to the fact that the seeds have different characteristic sizes. Nevertheless, in these

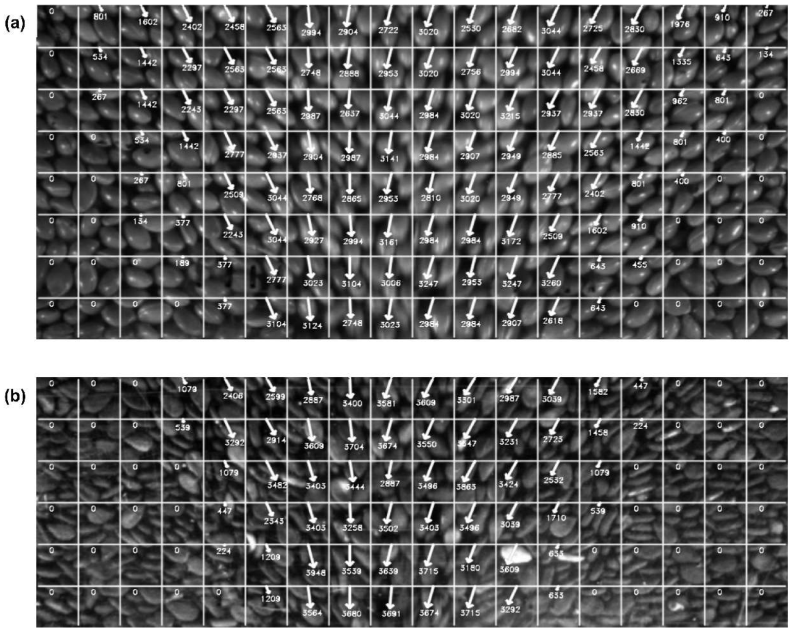

Fig. 4. Velocity field of the grains: (a) Millet (b) Black sesame.

Table 1. Execution times in seconds: (A) CPU implementation with simple image processing, (B) CPU implementation using neural network, (C) PYNQ-Z1 implementation with simple image processing.

(A) CPU [sec]				**(B) CPU NN [sec]**				**(C) PYNQ-Z1 [sec]**			
Frames	Seed			Frames	Seed			Frames	Seed		
	Millet	Black sesame	Canary seed		Millet	Black sesame	Canary seed		Millet	Black sesame	Canary seed
50	7.69	4.69	9.76	50	26.95	21.58	28.29	50	102.88	79.84	154.15
100	10.80	6.93	13.13	100	50.5	38.8	50.17	100	221.01	136.35	234.57
150	13.96	9.29	16.56	150	74.24	55.19	71.88	150	300.84	192.67	318.81
200	20.04	11.57	20.07	200	97.08	72.8	93.75	200	415.08	254.49	405.06

analyzed cases, the width of the outlet opening is different (to avoid blockages), thus, a more in-depth study should be carried out to analyze the dependence of the speed at the outlet with the size of the seeds and outlet width.

When comparing the displacements of the seeds found in the different interrogation windows through PIV with the ones determined visually, the differences result of the order of 10 %. Also, inside the hopper, these differences are more noticeable as we go closer to the walls of the silo. This may be due to the transition of the behavior: from fast discharge zone to stagnant zone. In this transition, the displacements of the grains are quite small and, some of them do not even move.

On the other hand, the enhancement stage improves the subsequent processing, and a trade off between pre-processing stage and its impact in the final velocity field must be taken into account. With the neural network, run times are longer than implementing the simple processing for the enhancement task, but using WESPE we can obtain more vectors in the final velocity field along the hopper.

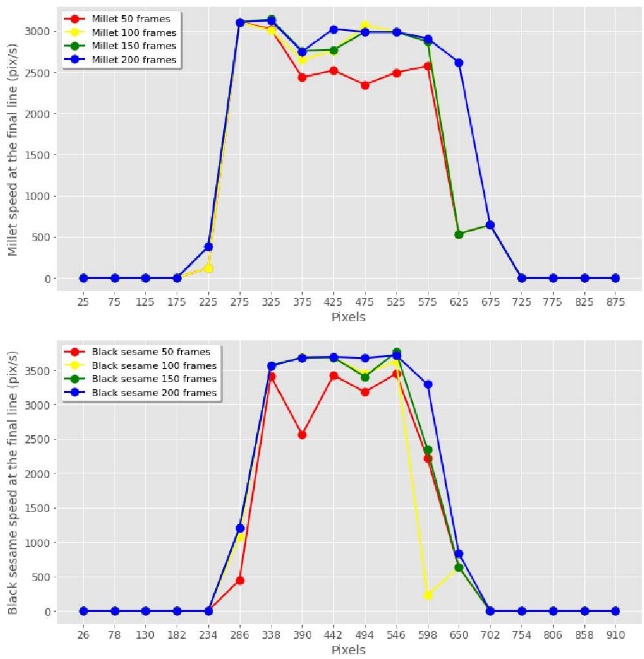

Fig. 5. Speed at the final line in pix/sec: Millet (top) and black sesame (bottom)

6 Conclusions and future work

In this work we developed an algorithm for the analysis of the motion of different granular materials within a silo hopper. Different stages were carried out in order to improve the motion detection. This goal was successfully achieved for all the tested cases and, in particular, the number of frames used in the process proves relevant to reduce fluctuations in the the obtained velocity. The algorithm was executed using different technologies (CPU and PYNQ-Z1) and different pre-processing methods in stage 1 (image processing and neural network). As expected, when comparing the execution times, they were lower for the case of the CPU implementation. Nevertheless, with these results and the new innovations for neural networks and FPGAs, in future work we can improve the execution times to get a good compromise between time processing and a solid pre-processing stage in order to generate a robust and precise velocity field. Also, future efforts will be dedicated to test more types of seeds, to process the velocity field in the entire silo (not only the area of the outlet) and to incorporate the version video camera in an embedded system.

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