CLASSIFICATION OF DYNAMIC SPECKLE SIGNALS THROUGH GRANULOMETRIC SIZE DISTRIBUTION

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Abstract — In this work we present a method based on granulometry, a tool derived from mathematical morphology, to classify dynamic speckle signals. Through the use of morphological operators we obtain a granulometric size distribution. From this distribution we obtain the related moments used as parameters to classify the image.

This technique enables the detection of differential activity in samples of sequences of dynamic speckle in space-time coordinates. The analysis of the method is illustrated through the detection of bruised regions in fruits. Finally, we present a discussion of the results.

Keywords — Dynamic speckle, mathematical morphology, granulometry, opening based granulometric size distribution.

I. INTRODUCTION

When the surface of an object, which has physical or biological activity, is illuminated with a coherent wave of light, the scattered light presents a granular structure, that is, spots of light and darkness randomly distributed, that change with time.

This phenomenon can be used to detect physical or biological changes in biological samples such as fruits (Pajuelo et al., 2003) and seeds (Braga et al., 2003), as well as in other non biological processes such as corrosion of steel and the process of drying of paint. The dynamics of the speckle effect is usually too complex to be described due to the multiple physical mechanisms that take place in it (Dainty, 1975; Erf, 1978), but the evaluation of this activity is a promising tool to monitor the evolution of the processes that take place in a biological sample and it is currently very used in medicine. It is then of great interest the development of techniques that allow to extract useful information from a sequence of images of dynamic speckle, also called bio-speckle.

This work presents an application of the granulometric size distribution to analyze the differential activity present in a sequence of bio speckle images. That analysis was applied to biological samples of apples with the purpose of studying the viability of the technique in the early diagnosis of damages on the surface of the fruit, before they were visible at plain sight.

This work is organized in the following way: in section II there is a brief description of the dynamic speckle phenomenon, the fundamentals of mathematical morphology (MM) and granulometric size distribution. At the end of that section we describe the steps to implement the proposed method and the experiments. In section III we analyze the results and compare them to other standard techniques for the analysis of these types of sequences. Finally in section IV we present the conclusions to this work.

II. METHODS

A. Dynamic speckle

When a surface presenting a certain physical or biological activity is illuminated by a wave of coherent light, as a laser beam, the scattered light presents a granular structure, i.e. bright and dark spots randomly distributed, that change along time, producing a visual effect such as that of a boiling liquid. Figure 1 shows a typical image. This effect is known as “dynamic speckle” – because of its changing dynamics – and it is the result of the coherent light dispersion through objects that exhibit some kind of activity. A sequence of images of this kind will present local intensity variations corresponding to the level of biological activity existing in the surface under observation.

Figure 2 shows a signal that corresponds to the evolution in time of the intensity or grey levels, of a pixel of the sequence of speckle images under study. Given the stochastic nature of the signal, it would be impossible, at plain sight, to recognize the correspondence of this signal to any particular area of the apple.

B. Mathematical morphology: Morphological operators

The two basic morphological operators in MM are erosion and dilation. Other operators can be defined by combination of the two basic operators (Matheron, Fig. 1. Typical speckle pattern
We describe some morphological operators used in this work for the analysis of bio-speakle signals.

A digital signal is a function:

$$f:D \subset \mathbb{Z} \rightarrow G \subset \mathbb{Z},$$

where $D$ and $G$ are $\mathbb{Z}$ subsets of integer numbers.

In the development of this work $f$ will denote a bio-speakle intensity signal.

The morphological erosion of the signal $f$ by the signal $b$, also called structuring element (SE), is defined in the following way (Matheron, 1975; Serra, 1982; Serra, 1988; Mukhopadhyay and Chanda, 2003):

$$\varepsilon(f, b)(s, t) = \min_{(s+x, t+y) \in D_b} \{ f(s+x, t+y) - b(x, y) \}$$

where $s, t$ are pixels in $D$. $D_f$ and $D_b$ are the supports of $f$ and $b$ respectively.

In an analogous way the morphological dilation of the signal $f$ by the signal $b$ or structuring element (SE) is defined as:

$$\delta(f, b)(s, t) = \max_{(s+x, t+y) \in D_b} \{ f(s-x, t-y) + b(x, y) \}$$

Based on the erosion and dilation we define the morphological opening as:

$$\gamma(f, b) = \delta(\varepsilon(f, b), b)$$

and the morphological closing as:

$$\phi(f, b) = \varepsilon(\delta(f, b), b)$$

Both the morphological operator and SE determine the characteristics of the resulting signal. In Fig. 3 we can see the effect produced by opening twice ($n=2$) the bio-speakle sequence shown in Fig. 2., by a flat SE.

As shown in Fig. 3, if the opening operator is applied to an original speckle signal $n$ times with flat SEs of increasing size we obtain a signal $f_n$ filtered or smoothed, removing in each iteration the “peaks” of the signal that fall above the structuring element (Dougherty and Astola, 1994). These operations are repeated until the resulting signal is no longer modified, that is for $n = N$. Specifically, for $n = 0$ we obtain the original signal.

If we call $\Omega(f_n)$ the area under the signal $f_n$ and $\Omega(f_0)$ the area under the original signal, we define the granulometric size distribution (GSD) of $n$ as

$$\phi(n) = 1 - \frac{\Omega(f_n)}{\Omega(f_0)}, \quad n = 0, \ldots, N$$

$\phi(n)$ or GSD is similar to a discrete cumulative function, as far as it is monotonic, except that does not reach 1 when it gets to idempotency.

This function represents the variation of the area of the resulting signal in each iteration.

Figure 4 shows the shape of $\phi(n)$, computed for $N=100$ for the bio-speckle signal of Fig. 2.

We want to analyze the viability of using the bio-speckle technique in the early diagnosis of damages on the surface of the fruit by applying Granulometric Size Distribution. In section D we describe some aspects of the experiment. Pajuelo et al. (2003) describes it in detail.

The images of dynamic speckle used in this work correspond to a portion of the surface of red apples. Even though the apples were bruised ex profeso, it was not possible to distinguish the bruised area from the rest of the fruit. An inert rigid object was included in the image as a reference.
C. Proposed tool

The application of the proposed tool can be summarized in the following steps:

- **Step 1**: Computation of Opening for the \( n \) value that produces the biggest difference between bio-speckle signals from different regions of interest.
- **Step 2**: Computation of the GSD associated with the Opening obtained in the first step.
- **Step 3**: By means of the value of the GSD calculated in step 2, classification of pixels to one of three zones: Hit, Regular or Pattern.
- **Step 4**: Image generation.

In the first step we apply the Opening with SE size that produces the maximum separation between zones. For these samples the best value is \( n=18 \).

From the resulting Opening applied in step 1, we calculate their GSD.

In the third step, we classify the pixels based on the values obtained in the previous step assigning them to one of three regions: reference (pattern), hit (bruised) or normal surface.

Finally, we generate a synthetic image with three different colors, one for each class.

D. Experiments

The experimental set up used to obtain the images is shown in Fig. 5.

A low power laser HeNe (5mW, \( \lambda=633nm \)) was used to illuminate the sample. An expanded divergent wave was used to illuminate a wide area of the fruit. The subjective speckle images were formed by an objective lens \( (f = 50mm, f/# = 16) \). Thus, the size of the mean speckle grains covers various pixels. Through the CCD camera connected to an acquisition plaque, successive images were stored in a PC. The laser was attenuated so that the irradiation effect on the sample was negligible. The laser illumination was adjusted to maintain constant the mean intensity in the image through the whole test. The bruise on the apple was produced by the fall of a steel ball (diameter=21.9mm, weight=133.6 g) from a height of 20cm. The damage on the sample could not be appreciated at plain sight.

For the development of this work, prior and posterior hit apple sequences of 256 images of dynamic speckle of 300 x 300 pixels were used, each one of them in grey levels, taken at an approximate rate of 12.5 frames per second.

III. RESULTS

The sequence of images described were stored in three-dimensional arrangements (300x300x256) where the third variable was time as represented by frame number. In this way the temporal evolution of each pixel could be analyzed to detect changes produced on the surface of the apple after the bruise.

Figure 5 shows an image ideally classified drawn by hand where we can see the three areas of interest of the bio-speckle sequence under analysis. This image was used to test our tool. We studied the characteristics of the three areas named reference inert zone pattern (in black, lower left corner), hit zone (in grey, right center) and regular zone (in white).

For the analysis we took three rectangular areas of 10x10 pixels each. GSDs for \( N=100 \) of each pixel were calculated and averaged for each zone.

Figure 6 shows the graphs corresponding to the mean value of the GSD obtained in each zone. It is clear that the curves for the three analyzed zones do not overlap.

The curves of the hit and regular zones are close to each other but separated from the pattern zone, which is to be expected because both areas show bio activity. We can see that for \( n=18 \) GSD gives, on average, the maximum separation of curves between the normal area and the bruised one. Thus, that value of GSD was used to classify all the pixels. To corroborate its per-
For classifying performance, we took several windows of each area (about 90 per zone) and we calculated the distribution of the mean values. In Fig. 7 we can see the result of overlapping the mean values of all windows.

By studying the GSDs in greater detail, we could see that $n = 18$ provides the maximum separation of the curves between the normal area and the bruised one. We used that value as the best one to classify the pixels into the three possible zones: hit, regular and bruised.

In Fig. 8 we can see the distribution histograms for the different classes for $n = 18$, superimposed to the theoretical Gaussian distributions. It is clear that the separation with the pattern zone is quite large, while the bruised and normal areas, although they are somehow superimposed, still allow for a satisfactory classification.

Figure 9 shows a classified image of the same region of the apple before and after the impact. Each area has been mapped into three levels of grey for a better visualization. In 9 a) and b) we recognize a black area corresponding to the inert reference, over the bottom left margin. In Fig. 9 b) we recognize a grey area of circular shape over the right center that corresponds to a bruised area. The regular area is represented in white.

To analyze the efficiency of the proposed tool we compare the classified image (Fig. 9b) to the image drawn by hand (Fig. 5). In the following table we summarize the percentage of hits of each zone.

<table>
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<tr>
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<th>Hits percentage of Bruised Zone</th>
<th>Hits percentage of regular Zone</th>
<th>Hits percentage of Reference Zone</th>
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<tr>
<td></td>
<td>86%</td>
<td>88%</td>
<td>99%</td>
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</table>
The efficiency percentage is quite high (higher than 85% for the regular and bruised zones despite their proximity).

As regards to processing times, if we consider that 90,000 sequences of length 256 must be processed for the case under study, the classification method is decisive for real-time applications development. Considering this objective and comparing this method to other previously used as Autocorrelation, Cooccurrence matrix, statistical cumulants, etc. (Pajuelo et al., 2003), it shows advantages due to the characteristics of the morphological operations, all of them algebraic operations over integer numbers of 8 bits. Thus, it is possible to implement algorithms and eventually hardware to obtain images in real time (Bangham and Marshall, 1998). Only one Opening operation for the best GSD curve place is required for the pixels classification.

Compared to methods of the type full-field like LASCA (Briers and Webster, 1996), it has the advantage of a better resolution for a window of the same size.

IV. CONCLUSIONS

Application of dynamic speckle techniques for the determination of bruising in apples has been previously considered using different approaches (Pajuelo et al., 2003; Passoni et al., 2004; Blotta et al., 2005; Federico and Kaufmann, 2006) and others with dissimilar but positive results. Our goal is to introduce morphologic tools to study speckle signals. We have proved that these techniques are valid and convenient because of the nature of theirs calculation (logical operations between integers numbers). Like EMD, granulometry is a sifting method, but computational cost is smaller. Good results have been obtained classifying the temporal sequences through the calculation of Openings to obtain the granulometric size distribution for each bio-speckle sequence, with a better level of detail compared to other methods that are more computation intensive (Blotta and Hidalgo, 2007). A new field of experimentation with this kind of signals is opened, however some illumination issues, related to the irregular shape of fruits, have to be studied to implement this method in a real world environment.

The application of this method could be useful especially if high resolution is required and the computational cost is an important factor, particularly when new instrumental is being developed (Konishi and Fujii, 1995). The morphological techniques have demonstrated to be advantageous with respect to other methods given that they require less computational power, by using basic arithmetic operations with integer numbers that are ideal for implementation in microcontrollers. These tools can also be directly translated to boolean algebra, and therefore are easily implemented in hardware for efficient integration into digital systems for faster processing (Bangham and Marshall, 1998).

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REFERENCES


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