Rough-Fuzzy Granularity in the study of optical phenomena

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Abstract

Granular computing deals with information representation in the form of a number of entities or information granules. Information granules are made up of a collection of entities, usually of numeric level, joined due to their similarity, functional adjacency, indistinguishability, coherence or alikeness. The granular computing is associated to sets concepts, such as fuzzy sets, rough sets, intervals.

In this work is considered the application of Rough-Fuzzy Granularity to the detection of optical phenomena in registered videos. Basically these phenomena are dynamic laser speckle and ecography videos.

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1 Introduction

In granular computing the information is grouped in entities that fulfill conditions of similarity, being the granules, conceptual entities that emerge as a direct consequence of the quest for the identification of abstract objects and its processing [Zadeh, 1970], [Pedrycz, 2001], [Yao, 2004]. The fuzzy sets and rough sets are a suitable way to define information granules.

The identification of information granules is context dependent and is expected that achieve two intuitive requirements: Justifiable granularity and Semantic meaningfulness. For numeric data, the requirement of Justifiable granularity is quantified by counting the number of data falling within the bounds of the granule, and the requirement of semantic meaningfulness is quantified by the length of the granule [Wang et al., 2015].

The dynamic laser speckle and ecography videos exhibit special characteristics.

Speckle is a phenomenon that allows to detect activity in several objects through the lighting with laser beams. Speckle generate an interference pattern formed by coherent radiation of a medium containing many sub-resolution scatterers in move. In order to register the phenomenon, successive images can be obtained with CCD cameras with a suitable resolution and in stable conditions [Rabal and Braga, 2008].

In ecography images, the speckles are a nuisance that is desired to diminish to improve recognition and resolution [Damerjiana et al., 2014], [Hiremath et al., 2013] .

In both cases, laser and ultrasound, a stable speckle pattern is achieved when the scatterers don´t move however when the sample has certain activity it is translated to the scatterers movement, the dynamic of the speckle pattern is used to evaluate the scatterer movements.

In this work we propose using a method based on rough-fuzzy granular computing to detect regions of interest in ecographies and Speckle image stack and also in single frames, since each of them would allow detecting different types of features. Then, temporal and spatial granularity is analyzed.

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2 Methodology

2.1 Granular Computing

In granular computing the information is grouped in entities that fulfill conditions of similarity, being the granules, conceptual entities that emerge as a direct consequence of the quest for the identification of abstract objects and its processing.. The fuzzy sets and rough sets are a suitable way to define granules.

In the signal processing, the information granules contribute to condensing a signal and represent it as a set of temporal granules through an abstraction mechanism that synthesizes the information. This representation preserves the granules identity in spite of some small fluctuations occurring within the experimental data [Bargiela and Pedrycz, 2003] . This type of condensation moves the signal from the numeric level up to the symbolic processing layer. The granules size and quantity implies a level of abstraction that is achieved (figure 1).

In spatial granulation the individual pixels of an image are arranged into larger entities and processed as such or density pixels with determined characteristic are analyzed in small windows. In small windows, the image is built with pixels computed as the sum of elements quantity belonging to the same fuzzy concept in a slide window of *NxN,* where the pixel is in the left-upper side. Thus, the image does not lose resolution, only it loses an edge of N-1 pixels (figure 2).

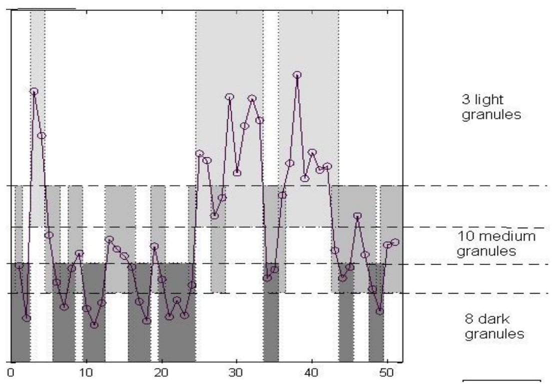


Figure 1. Temporal Fuzzy Granulation

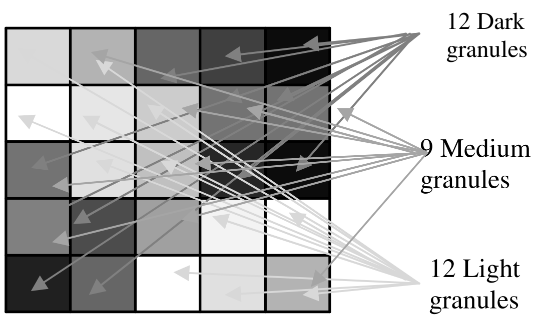


Figure 2. Spatial Fuzzy Granulation

2.2 Selection of Fuzzy-Rough sets

The theory of fuzzy sets, that permits the handling of vagueness and overlapped concepts, makes easy the adequate definition of intensity grains as they are inherent in speckle phenomena. By definition [Zadeh, 1965], [Dubois and Prade, 1980], given a Universal set U of elements u_i , a fuzzy set $A \in U$ is defined by pairs of elements (u_i, $\mu_A(u_i)$), where $\mu_A(u_i)$ is a real value in $[0,1]$ that represent the membership degree of u_i to A. In this case, the U set is given by intensity values $I(x,y) \in [0,255]$, and the fuzzy set are defined by membership functions $\mu_{Ck}(I(x,y))$, with $C \in$ {*dark, medium, light*} conceptual sets that define characteristics of the intensity pixels. These fuzzy sets facilitate the interpretation of subjective terms with indefinite limits.

A rough set is an approximation of a vague concept by a pair of precise concepts. Rough sets are based on the fact that an object cannot always be defined in precise form (crisply) inside a category on the basis of the value of its attributes.

Formally a rough set is expressed as:

Given an information system $S = (U,A)$, with U the universal set defining all the objects to consider, the A set defining its possible attributes, the subsets $X \subseteq U$ and $B \subseteq A$, and an equivalence class $[x]_B$ which defines a relation in which elements in X are indiscernible from each other by attributes from B, a rough set is defined by the sets $\{x \in U: [x]_B \subseteq X\}$ and $\{x \in U: [x]_B \cap X \neq \varnothing\}$ which are denominated as *B-lower approximation* and *B-upper approximation* of X in B respectively. These rough sets are denoted as $\underline{B}X$ and $\overline{B}X$ respectively. The objects in $\underline{B}X$ are certainly members of B and the objects in $\overline{B}X$ are possibly members in B [Pawlak, 1982], [Pawlak and Skowron, 2007]. If B is a fuzzy attribute, the sets are *rough-fuzzy sets* [Jensen, 2002]

To define the fuzzy-rough regions for each C_k concept, image intensity histogram is analyzed to find an equitable distribution for the number of pixels that will correspond to each *lower approximation* and *boundary region* (figure 3).

To granulate a signal $TS_{(x,y)}$ of length n, corresponding to the (x,y) pixel, successions of equal equivalence classes $[i]_{Ck}$ are considered (*upper approximation*). A granule ends when an equivalence class membership is zero.

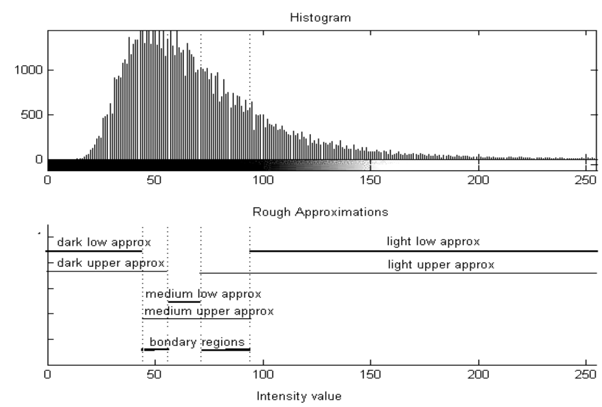


Figure 3. Rough Parameters selection

$$Gr_{(x,y)}(j,k) = \begin{cases} 1 \ \text{ if } \left[TS_{(x,y)}(j-1)\right]_{C_k} = 1 \text{ and } \left[TS_{(x,y)}(j)\right]_{C_k} = 0 \\ 0 \ \text{ in other case} \end{cases} \tag{1}$$

with j=1, n and k=1,2,3

The Temporal Rough-Fuzzy Granularity (*TRFG*) is computed as the granule quantities Gr in $j= n$ time for k equivalence classes. Eq (1) and (2)

$$TRFG(x,y) = \left(\sum_{k=1}^{3} \sum_{j=2}^{n} Gr_{(x,y)}(i,j) \right) / n \tag{2}$$

The Rough-Fuzzy spatial granularity *(SRFG)* is computed as the relative pixels quantities corresponding to equivalence classes $[i]_{Ck}$ in a window of $m*m$, where $P(x,y)$ indicate a pixel. Eq (3)

$$SRFG(x, y) = \left(\sum_{k=1}^{3} \sum_{i=0}^{m} \sum_{j=0}^{m} \left[P(x+i, y+j) \right]_{C_k} \right) / (m * m) \qquad (3)$$

The computed pixel value will be greater when the window pixels belong to the boundary regions (the pixel belongs to more than one fuzzy concept). This feature could be interpreted as corresponding to the blurring of moving regions.

3 Experiments

3.1 Speckle

Speckle is an optical phenomenon that takes place when a beam of coherent light (laser) illuminates an object with a surface that is rough in comparison with the wave length. Light is scattered in all directions and an interference pattern of granular aspect, called 'speckle pattern' can be observed on a screen. When the object under study presents some type of activity, such as biological specimens or certain physical phenomena, the particles of the surface move and the speckle pattern changes over time. This change permits the detection and segmentation of different activity degrees in a diversity of phenomena, allowing us to analyze paint drying time, imperceptible bruises in fruits, viability of seeds, bacteria mobility, endosperm phase proportions, etc. [Rabal and Braga, 2008], [Briers, 2007].

Stacks of records of successive images are obtained with CCD cameras with a suitable resolution and in stable conditions. The variation of each pixel value over time, considered as a time series, can be analyzed by applying different technologies of signal processing to obtain values that describe its behavior. The set of the values or descriptors obtained in every pixel generates an image whereby it is possible to detect regions with different characteristics.

Many of the methods has been studied to analyze dynamic speckle patterns require a high number of images to obtain good results. In some cases, the time of evolution of the analyzed activity is not known a priori and changes inside the time required for the register are lost. Also, records taken beyond the end of the studied events reduce the efficacy of the analysis because of the recording of assumed activity that has already finished, changed or reduced. Non-stationary phenomena cannot be detected.

require the register of images stack where the time history of each pixel is analyzed as a time series [Rabal and Braga, 2008]. Less frequent, single frame estimation techniques, such as local spatial contrast measurements [Briers, 2007] have been reported and used in actual applications with the advantages of being able to follow non-stationary processes.

The temporal granular computing has been applied to obtain descriptors in dynamic speckle, it provided satisfactory results in the detection of regions with different activity characteristic [Dai Pra et. al, 2009], besides, can perform almost real-time analysis of unquestionable importance in the inspection of biological, physical and / or chemical processes [Todorovich et al., 2013].

3.2 Ecography

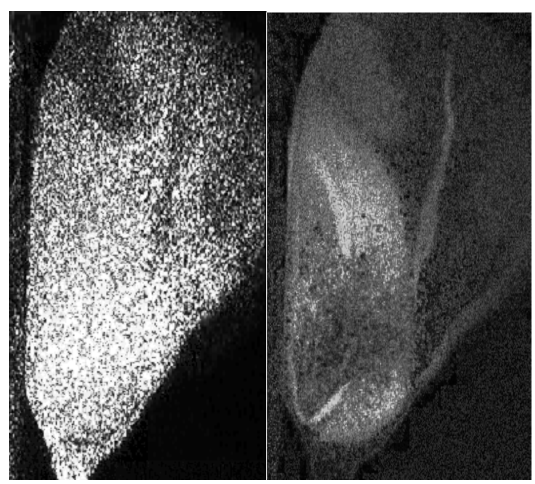
Usually, speckles observed in ultrasound images are only an artifact, a nuisance that is desired to diminish to improve recognition and resolution. In that direction most efforts were directed. To improve the performance of that technique, the instruments are usually provided with filters that smooth slow speckle motions effects, thus avoiding the dynamics that constitute speckle.

In both cases, laser and ultrasound, a stable speckle pattern is achieved when the scatterers don´t move, therefore the dynamic of the speckle pattern is used to evaluate the scatterer movements.

Activity measurement has shown a noticeable increase in research interest in the last few years. Laser speckle patterns show dynamic behavior when one or more mechanisms act on the observed sample, such as: Doppler Effect, diffusion, optical polarization activity [Briers, 2007].

4 Coments and results

Figure 4 a) shows a speckle patterns of a corn seed.. Figure 4 b) shows the identification of vital region of the seed (radicle and embryo). It´s important in the agricultural trade.



a) b)

Figure 4. Corn seed

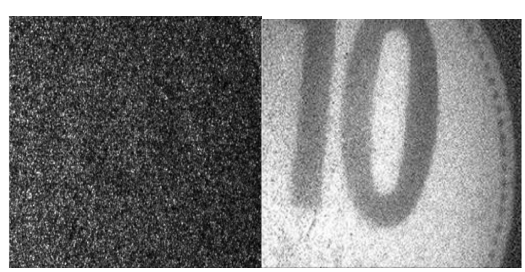
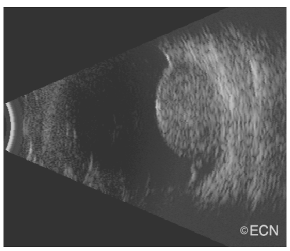


Figure 5. Painted coin

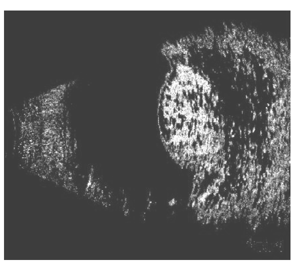
Figure 5 shows the result of the processing of a coin with a coat of fresh paint. The zones with relief have more activity and this allows to visualize the different reliefs of the coin. This experiment is very useful in the study of times of dried of paintings.

Figure 6 a) shows a ecography of eye tumor. Figure 6b) is the result of a temporal process, a semi posterior oval region with, seemingly, light dots in the middle that can be estimated could be blood vessels of neo-vascularization (Doppler effect), making very simple the differentiation between both pathologies.

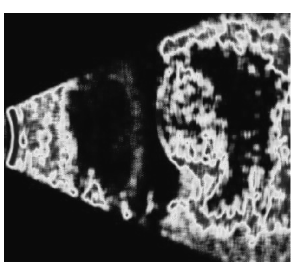
Figure 6c) is the result of a spatial process, retina can be seen that cannot be perceived in the other images.



a)



b)



c)

Figure 6. Eye melanoma

Figure 7 shows pulmonar ecographies that allow to evaluate the efficiency of the maneuver of alveolar recruitment across a dynamic monitoring, optimizing the strategy ventilatoria during the general anesthesia. The processing of the video would allow the quantification of the re-aeration and of the loss of pulmonary aeration, in order to contribute to not subjective elements in the interpretation of results.

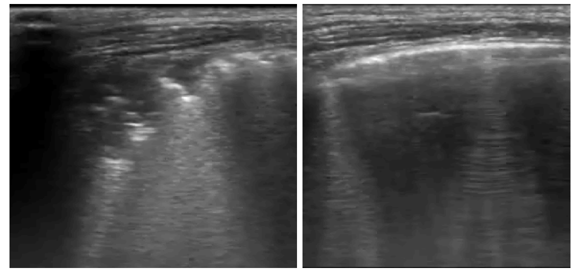


Figure 7. Pulmonar ecography

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