Chapter 10

Applications of the Use of Infrared Breast Images:

Segmentation and Classification of Breast Abnormalities

Marcus Costa de Araújo
https://orcid.org/0000-0002-1818-5686
Universidade Federal de Pernambuco, Brazil

Kamila Fernanda F. da Cunha Queiroz
https://orcid.org/0000-0003-4257-5155
Federal Institute of Rio Grande do Norte, Brazil

Renata Maria Cardoso Rodrigues de Souza
https://orcid.org/0000-0002-2849-1273
Universidade Federal de Pernambuco, Brazil

Rita de Cássia Fernandes de Lima
DEMEC, Federal University of Pernambuco, Brazil

ABSTRACT

Applications that have already been developed on using infrared (IR) imaging are proposed for a better understanding of breast cancer analysis. The first part of this chapter presents the use of interval data to classify breast abnormalities. Authors have been adapting machine learning techniques to work with interval variables that can handle the intrinsic variation of data. The second part evaluates segmentation techniques applied to breast IR images. Many authors use automatic image segmentation techniques that must consider the natural anatomical variation between people. Manual segmentation techniques can be used to minimize the problem of anatomical variations. The main purpose of such techniques is to seek to avoid the errors due to the natural asymmetry of the human body. A process that uses ellipsoidal elements to represent each breast has been chosen. The manual technique is more precise and can correct possible failures presented in the automatic method. Validation of each segmentation type was also included by using Jaccard, DICE, False Positive, and False Negative methods.

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STATISTICAL CLASSIFICATION OF BREAST ABNORMALITIES USING INFRARED (IR) IMAGES: INTERVAL CLASSIFIERS

This topic uses interval data to classify breast abnormalities. Many authors have been adapting some machine learning techniques to work with interval variables. These kinds of variable can handle the intrinsic variation of data. In breast thermography, the use of interval data along with machine learning techniques can lead to results offering new possibilities for their use.

The IR images were acquired at the Outpatient Clinic of Mastology of the Clinical Hospital of the Federal University of Pernambuco (HC/UFPE). The project was registered in the Brazilian Health Ministry (CEP/CCS/UFPE nº 279/05) after being approved by the Ethics Committee of UFPE.

Symbolic Data

In classical data modeling, each variable is represented by a single value, which makes the analysis of complex problems involving large data sets restrictive. In contrast, a symbolic variable can represent values which are multivalued, categorical, interval, frequency histograms and subsets and functions of different semantics, such as frequency, probabilistic, and possibilistic semantics.

Symbolic objects are defined for the purpose of reducing the volume and complexity of the original data by providing a new description of such data. According to Gowda and Diday (1992), symbolic objects are an extension of classical data. In conventional databases, objects are "individualized" whereas in symbolic databases they can be "united" by means of relationships. They therefore represent a group of data that is more complex than conventional data.

This chapter focuses on using symbolic objects of an interval nature.

Symbolic Interval Objects

Let Γ be a set of symbolic objects and let $\dot{\boldsymbol{y}}_i$ be an individual belonging to Γ. Let $\dot{\boldsymbol{y}}_{i1},\ \dot{\boldsymbol{y}}_{i2},\ldots,\dot{\boldsymbol{y}}_{i3}$ be a set of p symbolic variables that describe the object $\dot{\boldsymbol{y}}_i$. A symbolic interval object $\dot{\boldsymbol{y}}_i$ is one where the variables assume values within an interval (Schnepper & Stadtherr, 1996)., i.e.,

$$\dot{y}_{ij} = \left[a_{ij}, b_{ij}\right] \subset R; a_{ij} \le b_{ij}; a_{ij}, b_{ij} \in R; j = 1,\ldots,p$$

According to Silva and Brito (2006), the use of interval data is justified for two different situations:

1. Let there be a dataset Ω ,, which has been aggregated to a base that uses certain criteria. Each element of Ω is described by real variables $\boldsymbol{x}_j,\ \boldsymbol{j} = 1,\ldots,\boldsymbol{p}$, and the interval variables $\dot{\boldsymbol{y}}_j$ represent the variability of $\boldsymbol{x}_j$ in each group of data.
2. Each interval variable $\dot{\boldsymbol{y}}_j$ represents a set of possible values within the uncertainty of measurement of the real variable $\boldsymbol{x}_j$.

Thus, a source of interval data can naturally arise from the description of specific technical data.

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