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Intelligent retrieval and classification in three-dimensional biomedical images — A systematic mapping[☆]

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HIGHLIGHTS

- A systematic mapping covering intelligent retrieval for 3D medical images.
- Descriptors focusing in shape are widely developed.
- 3D medical images use computing techniques from 2D domain, limiting the results.

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ABSTRACT

The massive generation of data has raised new research topics, such as methods to store and to retrieve large volumes of information. Some medical image modalities, such as Magnetic Resonance Imaging, generate hundreds images series and many research groups have presented studies to develop intelligent techniques to classify and to retrieve this information. However, these studies are dispersed in several databases, and cataloged by using different terms. In this paper we present an analysis of these studies, through a Systematic Mapping that identifies methods and techniques currently being used in this scenario. In addition, we provide a perspective about the type of scientific literature the researchers have been disclosed their studies as well as impact on the scientific literature in dissemination of this knowledge domain. Some challenges and research opportunities are also highlighted in order to propitiate advances in the area.

Contents

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1. Introduction

The amount of data generated by our society has grown exponentially. From 2005 to 2020 it will increase from 130 exabytes to 40,000 exabytes, or 40 trillion gigabytes [1]. In Healthcare, this scenario is similar: in 2009 it was estimated about 434 pentabytes data storage only related to Healthcare in United States, and unlike other sectors where big data is represented mostly by text, this sector also stores medical images, generating individual exams with large volume of data [2]. In 2020, about 25.000 petabytes of information from Healthcare, related to digital data and patient records are expected [3]. Considering this scenario, many researchers have proposed intelligent methods to process, classify or retrieve these data to make them available immediately wherever and whenever necessary.

Many of the intelligent retrieval systems implement methods that use metadata-based approaches to retrieve objects from image databases. This type of retrieval requires that the user employ keywords which will be used as parameters. Consequently, this method may contain flaws, due poorly chosen keywords, subjectivity of the content searched, among others. Systems dealing with medical image content can be an alternative for meta-data searches. The "content" in this scenario consider characteristics extracted from the image related to aspects such as color, texture and shape [4].

Medical exams are currently more complex and can generate a large volume of data to be analyzed by experts. Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single-photon Emission Computed Tomography (SPECT) are examples of medical modalities that can generate hundreds of slices in a single exam [5]. In order to make a correct diagnosis, a careful investigation is usually conducted on each slice. The analysis of these two-dimensional (2D) images, even using an automated process, can be highly time-consuming. To minimize this problem when the process is automated, two main approaches have been frequently used: optimizing the feature extraction from 2D-slice sets or extracting features directly from three-dimensional (3D) objects [4]. The latter approach results in systems named 3D Content-based Image Retrieval (3D CBIR), model retrieval, 3D object retrieval or simply 3D image intelligent retrieval.

Some previous reviews were published regarding this theme. In a time perspective, the first work published was Müller et al. [6], which provided an overview of medical images retrieval, exploring 2D features, and pointing out 3D domain as "future trend". In Datta et al. [7], the focus was on CBIR in several domains, such as medical images, engineering, and arts. The authors offer an overview of the publications of this subject and tried to map the main techniques used for this purpose. Akgul et al. [8] and Hwang et al. [9] presented the state of art of CBIR in medical images with emphasis mainly on 2D descriptors and similarity functions. Kumar et al. [10] offer an advance in CBIR techniques applied to medical images, with special attention to the 3D domain, but focusing on search of key slices of the same volume. Finally, with the advent of deep learning in medical image processing, Litjens et al. [11] provide a survey about this technique and how it is used in different image processing domains — segmentation, registration, classification, and retrieval.

This Systematic Mapping is innovative since it provides an updated review of processing and retrieval from a 3D perspective considering the medical image domain. Besides including more recent studies, a Systematic Mapping was conducted, which allows reproducing and auditing the search. Additionally, different from previous reviews about this subject, we also performed an analysis about the studies quality using some well-known metrics such as H5-index impact factor and the scientific literature where the studies were published.

Furthermore, we provide a critical perspective about this subject since we made an effort to answer these questions: are the researchers producing relevant studies in this area? Where are the researchers publishing their studies? Is the Healthcare area really being benefited from the retrieval and classification techniques?

For achieve the answers of these questions we analyzed the included papers through different perspectives: (1) papers quality through h5-index metric and by the papers content such as quality of methodology description and results reported; (2) descriptors used; (3) similarity comparison methods applied; (4) indexing methods used to store the feature vectors; (5) databases used by the author to validate their approach; (6) the proposal of the techniques developed, and (7) the evaluation metrics used in the included papers.

Besides CBIR studies, we also investigated classification problems that produce innovative descriptors and different methods to classify the 3D medical objects or images. When it is mentioned 3D graphic structures, i.e., surface or volume resultant of a reconstruction process, we refer them as 3D medical objects. When the graphical objects are related to 2D images (slices from 3D exams, such as MRI or CT) we refer them as medical images.

This paper is organized as follows: Section 2 explains our research method — the Systematic Mapping, presenting some topics considered in this research process. Section 3 presents a quantitative and qualitative global analysis about the papers related to classification and retrieval in 3D medical objects or images, and a high level view about the studies quality. Sections 4–6, respectively discuss descriptors, indexing methods, and methods for measuring the similarity developed in the articles included along the research. Section 7 presents the medical images databases found in the papers selected. Section 8 discuss the main problems solved by computational techniques, and Section 9 details evaluation metrics cited by the studies included. Section 10 discusses the results found and maps some trends for this knowledge field. Finally, Section 11 presents the final conclusion.

Table 1
Strings used in each scientific library and amount of retrieval papers.

Database	Search string	Results
IEEE	similarity retrieval AND 3D and medical	25
	CBIR AND MRI	22
	CBIR AND CT	32
	descriptor medical 3D	53
	image retrieval AND medical AND 3D	171
	3D medical volume retrieval	30
	3D medical surface retrieval	37
PubMed	(“model retrieval”) OR “3D CBIR” OR (“image retrieval”[Title/Abstract] AND 3D)	34
	descriptor AND 3D AND retrieval	25
	similarity retrieval AND 3D	63
Science Direct	(image retrieval AND medical) and TITLE-ABSTR-KEY(3D).	82
	CBIR AND (CT or MRI)	353
	TITLE-ABSTR-KEY(3D medical) and (volume retrieval)	84
	TITLE-ABSTR-KEY(3D medical) and (surface retrieval)	65
	TITLE-ABSTR-KEY(descriptor) and (medical 3D)	428
	“similarity retrieval” AND 3D AND medical	69
ACM	(Abstract:image and Abstract:retrieval and Abstract:medical and Abstract:3D)	26
	CBIR AND (MRI or CT)	97
	“similarity retrieval” and 3D and medical	94
	(medical 3D) and (Title:descriptor)	37
	(Abstract:3D and Abstract:medical and Abstract:volume and Abstract:retrieval)	8
	(Abstract:3D and Abstract:medical and Abstract:surface and Abstract:retrieval)	11
SPIE	ABSTRACT:(3D) AND ABSTRACT:(medical) AND ABSTRACT:(retrieval)	27
	ABSTRACT:(medical descriptor) AND ABSTRACT:(3D)	11
	ABSTRACT:(medical) AND (“volume retrieval”)	1
	(“similarity retrieval”) AND ABSTRACT:(medical)	1
Springer	“image retrieval” or “model retrieval” AND (medical) AND NOT (Overview or semantic)	47
	3D AND medical AND (“image retrieval” or “model retrieval”)	29

2. Research method

Systematic Mapping, also called *scoping review* is defined by Petticrew and Roberts [12] as a review that evaluates the types of studies, the date on which they were made, and where they are located. It presents a methodology which can be reproduced and audited by other researchers, as well as provide a general overview of complex subjects. Three phases are usually defined: planning, conduction and data extraction.

The planning phase is very similar to the Systematic Review [13]. At this stage some topics are defined such as review questions, keywords, scientific libraries, inclusion and exclusion criteria. In the Conduction stage each paper is evaluated accordingly to the inclusion and exclusion criteria defined in the protocol. Finally, during the extraction phase the studies are deeply analyzed aiming at classifying and categorizing data about the subject.

2.1. Planning

At this stage, we defined the main topics to outline the research, such as the questions that this study proposes to answer:

1. Which descriptors and methods for measuring similarity are being used to retrieve and to store 3D medical objects or images?
2. Which data structures are used for descriptors representation?
3. What methods are used to evaluate these processing and retrieval techniques?
4. Which types of medical images are being analyzed?
5. Which are the practical applications these techniques are developed for?
6. Is there relationships between the techniques developed and the medical images or anomalies?

The databases selected for this Systematic Mapping were: IEEE Xplore, ACM Digital Library, Science Direct, SPIE library, SpringerLink and Pubmed. We did not limit a period for the search but the newest papers returned in this Systematic Mapping are from January 2018. We considered only papers written in English. The keywords, search strings and the number of results found in each database are presented in Table 1.

2.2. Conduction and data extraction phases

After retrieving the papers from the databases, we applied the following Inclusion (I) and Exclusion (E) criteria listed in Table 2.

To evaluate whether an article would be included in this study, the following rules were elaborated considering the type of article and the inclusion and exclusion criteria presented:

- (I1 OR I2 OR I3) AND (NOT(E1 OR E2 OR E3))
- (I4 AND (NOT (E1))

During this phase, we followed some guidelines in the papers evaluation process: firstly, the studies that investigate molecules shape classification and retrieval are not included because these 3D objects are not reconstructed from medical images. In this sense, we considered “3D medical object” only the sets of 2D slices, such as from MRI and CT, the 3D object meshes with the surface reconstructed or the 3D object represented in a voxels grid. Thus,

Table 2
List of Inclusion and Exclusion criteria.

Criterion	Description
I1	Conceptualizes descriptors or similarity comparison methods for 3D medical objects or medical images classification and retrieval.
I2	Conceptualize techniques to improve results of the content-based searches.
I3	Evaluates methods for 3D medical objects classification and retrieval.
I4	Details medical databases and state of the art or reviews about this subject.
E1	Focus is different from 3D medical objects.
E2	Papers that do not develop classification and retrieval techniques.
E3	Uses retrieval and classification techniques for tracking or video retrieval.

this type of studies were excluded by the first exclusion criterion (E1). Secondly, as the purpose of this paper is to evaluate the retrieval and classification tasks, papers that performed segmentation, reconstruction, tracking and modeling were excluded by E3 criterion. Finally, we analyzed individually papers that executed face recognition and retrieval, in order to validate if the object was reconstructed from MRI or CT images; papers that extracted features from a face multi-views images were also excluded.

We also defined quality criteria applied to the papers included. The main goal of these criteria is to analyze characteristics of the papers included and to score them both to compose an additional exclusion criterion, and support us on the analysis of the relationship between the article and the publication quality.

If an article completely satisfies a quality criterion, it gets value 1 for the item; if the criterion is partially satisfied, the article receives value 0.5 for the item, and the value zero is assigned if the criterion is not satisfied for that item. A weight is assigned for each criterion so that the sum of an article can range from 0 to 4. Table 3 presents the quality criteria used in this Systematic Mapping.

We found 1962 papers, from which 520 were duplicated (the same papers were found from different search strings), one was not in English. After applying the Inclusion/Exclusion criteria, we obtained 121 papers selected for the Data Extraction phase. At this stage, we applied the quality criteria and papers with score below 3.5 were excluded.[1] Thus, we selected 107 studies that will be presented and discussed in the next sections.

3. Global analysis

Before starting the studies analysis it is important to highlight the differences between CBIR and classification techniques, since these differences guided us on the papers categorization.

For image classification problems, there are labeled classes in which objects retrieved are classified. In CBIR there are not labeled classes and the algorithm efficiency usually is calculated based on the first images retrieved and their similarity with the image given as query [4]. For example: if the user gives a flower image as query, we can consider a perfect classification if the result return all flowers images stored in the database. In this example, the scope is correctly retrieve flowers and no-flowers. For retrieval purposes we consider a perfect retrieval if the first images retrieved are flowers **and** they must have the same attributes (color, shape, etc.). In retrieval problems the search context is more specific.

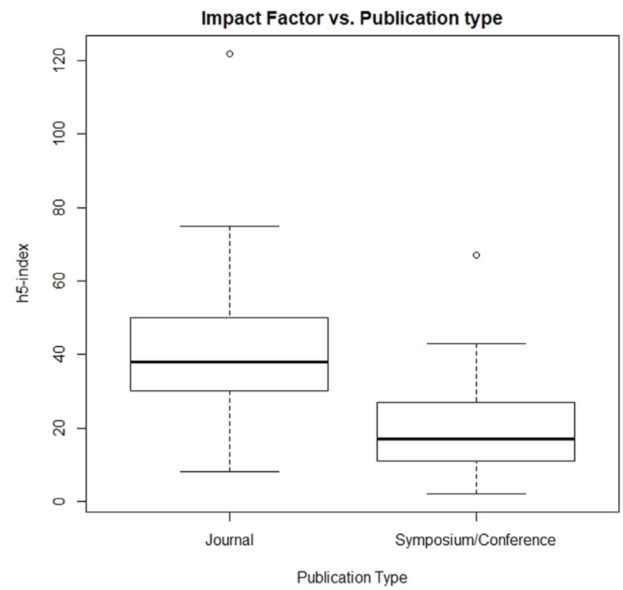


Fig. 1. Relationship between Publication type and h5-index distribution. Journals in which the papers selected were published present higher h5-index when compared to Conferences.

The 107 studies included were distributed into categories considering the retrieval and classification techniques. The distribution of each technique was 62% for classification, 32% for CBIR, 1% exploits databases for 3D medical objects and other papers such as review ones represent 5% of the papers selected.

Besides understanding how computational techniques are applied to store and retrieve 3D medical objects or images, we also verified what kind of scientific literature the researchers are publishing their works in. Fig. 1 shows a difference between Symposiums/Conference and Journal publications when the h5-index is considered. A percentage of 53% of the papers selected were published in Symposiums and Conferences, while 47% were published in Journals. The h5-index average of the articles included[2] was higher in Journals (average of 38) than in Symposiums (average of 17).

In addition, we ranked the top 10 scientific literature according to their h5-index and (Table 4). Both Fig. 1 and Table 4 indicates that studies on this knowledge area have attracted the scientific community and generated relevant contributions, since we note papers published in the scientific literature with high h5-index in Engineering, Physics, Computer Science and Mathematics knowledge domains [14].

The application of quality criteria in the papers included showed that the publication with the higher h5-index (Neuroimage, with a h5-index of 120) had a article published that was evaluated with the maximum score (4) in the quality criteria indicating that the studies have well defined goals and the results were evaluated suitably. (See Fig. 2.)

As mentioned in Section 1, this Systematic Mapping focus on CBIR and classification of 3D medical objects structure. Fig. 3 shows each of these techniques related to their respective h5-index average. We verified that articles dealing with classification problems

[1] The list of each paper evaluated following the inclusion and quality criteria defined below can be find in the URL: http://www.lapis.each.usp.br/Bergamasco_SM/SystematicMapping.xls.

[2] In this study we used the h5-index as metric instead of the Journal Citation Report [14], which is well-known among researchers. The study of [15] pointed out a strong correlation between the two metrics using Spearman's correlation (0.718 ($p < 0.000$)). The advantage of h5-index is that it can be calculated for both Conferences and Journals. The h5-index metric is composed by the total number of publications and the total number of citations to those works. For example: if an conference has h5-index = 30 it means that this conference has 30 papers with at least 30 citations in the last 5 years.

Table 3
Quality criteria and weights.

Criteria	Description	Weight
QC1	The study proposal is clearly described	1
QC2	There is a clear technique explanation including implementation, evaluation method and/or review methodology.	1
QC3	The study describes the goal or the importance of its research.	1
QC4	The study presents evaluation of the technique or method developed.	0.4
QC5	The results are reported	0.6
	Total	4

Table 4
Ranking of top 10 publication type and their respective h5-index. Periodicals and Conferences that published four or more of the studies were included in this list) (J = Journal and S = Symposium or Conference).

Publication title	h5-index	Frequency (# of papers included)	Type
Neuroimage	122	3	J
Information Sciences	75	1	J
International Journal of Computer Vision	68	1	J
IEEE International Conference on Acoustics, Speech and Signal Processing	67	1	S
Medical Image Analysis	49	3	J
Pattern Recognition Letters	46	2	J
Computer Methods and Programs in Biomedicine	38	2	J
IEEE International Conference on Image Processing (ICIP)	38	2	S
Academic Radiology	35	4	J
Medical image computing and computer-assisted intervention (MICCAI)	34	4	S

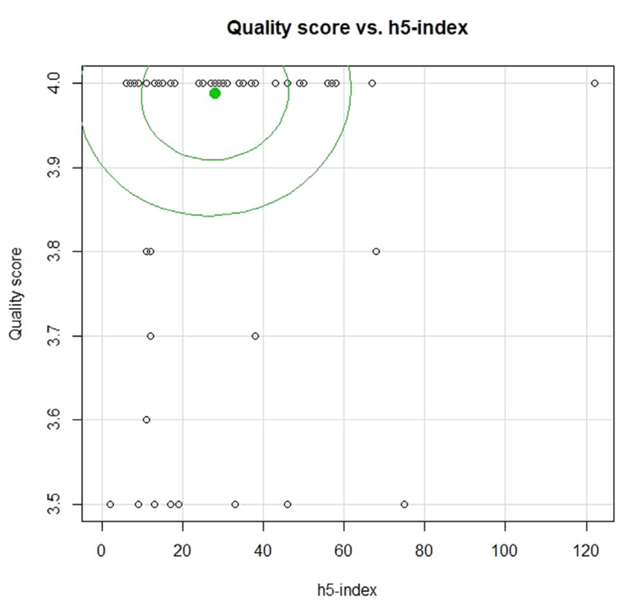


Fig. 2. Relationship between the score obtained in the quality criteria evaluation and the h5-index distribution.

succeed into publishing in scientific publication with higher h5-index. About 44% of classification papers were published in scientific journals or symposiums with h5-index higher than 30, while papers focused on CBIR techniques have about 21% of publications in this h5-index range. Regarding these findings, our main hypothesis is that there are more well cited periodicals in the classification area because this field is older as research topic, while CBIR is more recent. Thus, it could be natural that there are less high impact specific periodicals for the latter subject. However, we noted that the initial year of publication in high h5-index periodicals of the papers included was 2009 for both topics (h5-index greater than 40).

The authors of the included studies focused their researches mainly on descriptors development and analysis: 89% of the papers dealt with new descriptor proposals [16,17], or performance analysis of different descriptors for a particular scope [18,19]. Thus, we can conclude that the descriptors extraction and analysis is an important task for both classification and retrieval techniques.

In medical image researches, it is possible to apply descriptors in 2D or 3D domains. Here, we consider 3D descriptors only those implemented for extracting features of 3D medical objects (with surface or volume reconstructed). Descriptors applied to a set of slices of the same volumetric object are considered 2D because they usually process 2D information (area, contour, pixel gradient, among others) [20,21].

Fig. 4 shows that papers related to classification and retrieval of 3D medical objects has increased year by year from 2009 until 2013, as well as the number of specific papers presenting 3D descriptors. However, two-dimensional descriptors remain important to this research area: about 30% of the 2D descriptors developed were applied mainly for slice retrieval [22] and alignment. In the case of brain images, it is common use 2D descriptors to detect tumors and Alzheimer disease [23,24,18]. Despite these numbers, some authors reported that 2D approaches can be highly time-consuming, since it is necessary to analyze many slices to have the complete information about the problem under investigation [25–27].

Table 5
Descriptors categories according to [4] and their respective advantages and disadvantages.

Category	Advantages	Disadvantages	Papers classification
Statistical-based	- Faster, invariant to rotation and robustness - Robust against noise	- Spatial information not preserved - Small differences are not distinguished	[28–52,17,53,54]
Geometrical-based	- Good representation of 3D surface or voxels in the object analyzed - Easy implementation	- Difficulty in creating efficient indexing methods - Sensitive to small noise	[55–59,47,60,17]
Signal-based	- Easy implementation	- Requires pre-processing before feature extraction	[61–68,16,69–71,59,72–77]
Topology-based	- Intuitive representation of 3D object shape structure	- Time-consuming	[78,48,79]
Appearance-based	- High level description of surface color and texture	- This information is not enough to differentiate 3D objects. Usually needs to be complemented by other descriptors	[80,29–33,38]
Visual-based	- Reducing the descriptors development difficulty, since this descriptor works with 2D information	-Time-consuming (one 3D object could have several projections/slices)	[81–87,20,88,27,89–104,18,105–126,24,127–156,23,157–169,26,170–176]

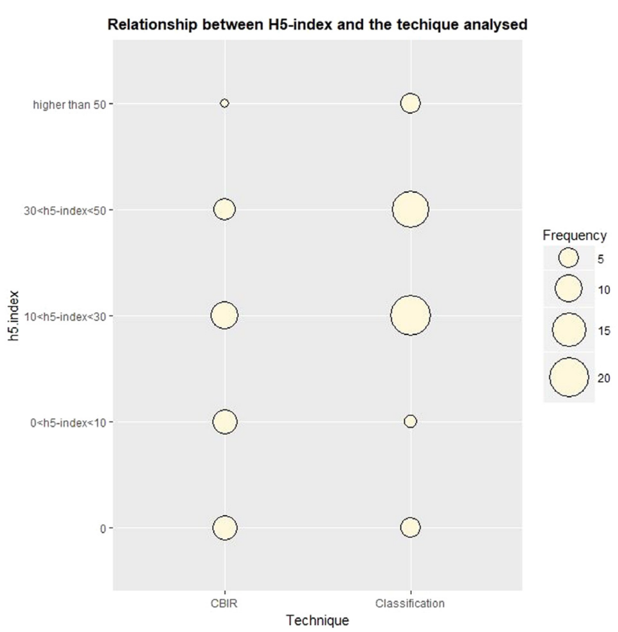


Fig. 3. Techniques distribution per h5-index value: CBIR and classification.

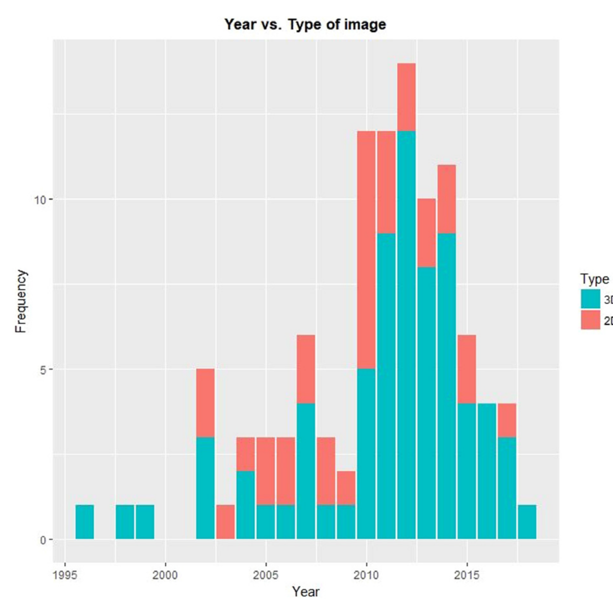


Fig. 4. Relationship between the descriptor type domain type studied in the papers selected and their respective year of publication.

Due to medical imaging technology advances, volumetric exams such as CT, MRI and PET modalities became more popular and, consequently, we observed a large increase of data to be stored. In this review, 35% of the papers used CT images, 36% used MRI images, 11% PET, and 8% combined different types of image modalities. More than 85% developed techniques considering information from the 3D domain, indicating the relevancy of developing techniques that deal with this considerable volume of data generated by these image modalities in a fast and accurately procedure.

Another topic of interest in medical image classification and retrieval is related to the database used in the researches. Since the data volume grown in the last decade, it is expected that the repositories to store 2D and 3D objects have also increased. However, in the medical image scenario we deal with information related to the patient health and their identity; there are hence ethical questions that can make it difficult release information to allows validate the results. This can explain the fact that 72% of the papers selected use particular medical images, provided by some hospitals and health centers. This can hinder the comparison among the techniques developed by different research groups. From the included papers, 42% studied a limited number of patients, not processing more than 50 cases [173,16,44]. Though we noted important databases which are used as benchmarks for the studies, highlighting the

Alzheimer's Disease Neuroimaging Initiative (ADNI),[3] and the Lung Image Database Consortium (LIDC) [177].

Since the aim of medical images classification and retrieval systems is commonly related to aid diagnosis, clinicians are an important piece during their development and evaluation. Meanwhile, just 4% of the included papers reported evaluations performed with experts [76,54]. Additionally, only 1% of the papers [153,127] reported the use of the technique developed in the daily clinical routine.

4. Descriptors

Descriptors are important pieces for both retrieval and classification problems. They are algorithms that extract characteristics of 2D or 3D objects in order to represent them in a manner that allows posterior comparison. For 2D images, we have a well-known taxonomy that establishes three categories: shape-based, texture-based, and color-based. For 3D objects, many of the descriptors developed are focused on extracting shape and texture information, mainly related to 3D object's structure and topology.

Specifically for medical images, researchers have predominantly worked with shape and texture features, but other approaches are available in the literature. In [4] a descriptors classification is provided, defining the following categories:

- *Statistical-based*: extracts sampling regions of the 3D objects and analyzes characteristics as curvature distribution, relationship among vertices, and moments of various orders;
- *Geometrical-based*: works directly with 3D objects data structure, and extracts information from their elementary unit such as vertex, polygon or voxel. It also considers the spatial domain, since it can separate 3D objects in sets based on their coordinates. Descriptors in this category include distance maps, ray-based, weighted point sets, among others;
- *Signal-based*: analyzes 3D objects from the frequency domain perspective. Examples are Fourier descriptors and Spherical Harmonics;
- *Topology-based*: consists in a high-level representation of how vertices are connected. The most common descriptors in this category are based on graph data structure and skeletons;
- *Visual-based*: the main idea of this category is mapping the 3D object on a set of 2D images. This is a popular technique in the medical field because a number of 3D medical objects are composed of slices; 2D descriptors are less complex and there are many descriptors already developed for the 2D domain;
- *Appearance-based*: descriptors of this category extract features based on surface color and texture. This category is normally applied together to shape descriptors to complement the information.

Table 5 provides summarized information regarding the descriptors classification found in the studies included. Statistical-based are predominant in the 3D domain. In [178], for example, the brain surface contours in Teichmüller space is used to analyze morphology alterations due to Alzheimer disease. Author of [38] proposes a Shape Context descriptor that calculates, for each vertex on the surface, the set of vectors originating from this vertex to all the other vertices forming a unique configuration of the entire surface of this vertex. Texture and shape descriptors are found in several works in the 2D domain. In [179] a good overview about descriptors in this domain is provided.

No relationship was found between the descriptor used and the characteristics of the medical image (anomaly investigated or part of the human body represented), but we noted that 40% of the papers using visual-based descriptors were focused on brain images [87,88]. Some descriptors were used more frequently, such as Spherical Harmonics in the Signal-based category, the 3D Moment Invariants in the Statistical-based category, and Wavelet Transform in the Visual-based category. These techniques are detailed in the next sections.

4.1. Spherical Harmonics

Spherical Harmonics (SH) is a frequency-based space that represents functions over a sphere. The SH is defined as the angular portion of a set of solutions to Laplace's equation using the spherical coordinates of the 3D object, organized by their angular frequency. For the specific case of Laplace's equation solution, the SH forms an orthogonal system [4].

Eq. (1) represents this case, where $Y_\ell^m(\theta,\varphi)$ is the Laplace's equation with respect to spherical coordinates (θ,φ); m and ℓ are complex integer numbers, and f is a square-integrable function. Fig. 5 shows a set of SH possibilities related to the values of m and ℓ.

$$f(\theta,\varphi)=\sum_{\ell=0}^{\infty}\sum_{m=-\ell}^{\ell} f_\ell^m\, Y_\ell^m(\theta,\varphi) \tag{1}$$

In [70], the authors used SH to map the left ventricle structure, reconstructed from SPECT images, into a sphere. Then, by using the normalized and invariant sphere, they compare the left ventricles in two different states (dilated and relaxed).

The authors of [74] use the same idea to compare the volume and shape in the amygdala–hippocampal between patients diagnosed with schizophrenia and normal subjects. The researchers discovered a closer correspondence between the shapes of the left and right amygdala–hippocampal complex in normal controls than they observed in patients with schizophrenia.

In [76] SH is applied to deformable 3D organs. In the first phase of the process, the deformation subspaces are identified in the SH domain. Then, they represent the deformed surface by a block sparse vector in a structured dictionary. The researchers compare the method considering different aspects such as computing time and accuracy, reaching a precision greater than 70% using Hausdorff distance.

4.2. 3D Moment Invariants

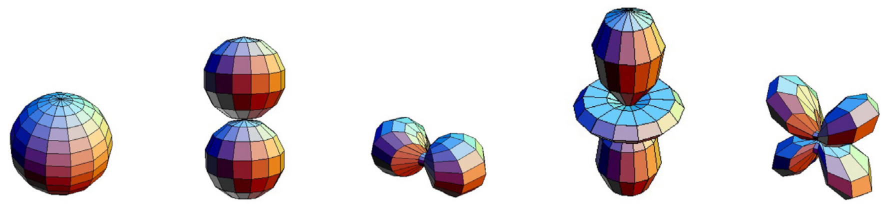
3D Moment Invariants are statistical descriptors that calculate shape characteristics (such as area and volume) of a 3D object regarding its translation and rotation [28]. 3D Moment Invariants can be related to both volume and 3D surfaces. For both cases, Eq. (2) is applied. This equation is directly inherited from 2D Moment Invariants, where M is the 3D object and the term M_{pqr} is the *(p, q, r)*th 3D moment. Each 3D object has a unique set of 3D moments [4].

$$M_{pqr}=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q z^r f(x,y,z)\,dx\,dy\,dz \tag{2}$$

In this context, in [42] this technique is applied in 3D bones micro-CT images to detect the distribution of osteocyte lacunae responsible to indicate several bones diseases. The authors compared their method with manual segmentation and statistical volume calculation. According to them, results show that the automatic extraction using 3D Moment Invariants reached 92.8% of similarity comparing with the ground truth.

Also, the study [49] investigates the correlation between the shapes of the cortical sulci and the sex and handedness of 142 brains exams generated by CT scan. They applied 12 first Moments

[3] Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu).



(a) ℓ=0, m=0 (b) ℓ=1, m=0 (c) ℓ=1, m=1 (d) ℓ=2, m=0 (e) ℓ=2, m=1

(f) ℓ=2, m=2

Fig. 5. Spherical Harmonics demonstration with complex constants variations.

Invariants to cortical sulci and found that moment invariant I_{33}^{3} shows that the sulcus of the right-handed population is deeper backwards, near the central sulcus than forward, in the frontal part, when compared to left-handed subjects. The authors also noted a significant correlation between sex and the distribution of the fourth moment invariant, in which the curvature associated to the S-shape of the sulcus is more significant for females subjects.

4.3. 3D Wavelet Transform

The 3D Wavelet Transform decomposes an image into different domains, such as frequency and time. Thus, the wavelet functions are powerful tools for signal processing [4]. It is broadly used in Visual-based descriptors to analyze the image texture, being useful to detect anomalies in which the appearance of normal tissues is different from that of abnormal tissues, such as tumors and Alzheimer disease.

The Wavelet Transform decomposes a 3D signal into four sub-bands regarding to columns and row images. These filters create a possible combination for each pair of column and row.

Eq. (3) presents the formulation of a wavelet coefficient of signal t $\Psi(t)$, a refers to scaling and b is the time. The multiplication by the factor $\frac{1}{\sqrt{a}}$ normalizes the energy in different scales.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) a \neq 0, b \in \Re \tag{3}$$

In the included studies of the present review, the 3D wavelet transform was used in different types of applications. In [21], authors investigate the interstitial lung disease in CT images using gray level histograms and wavelet-based features such as B-spline wavelet. Also, for the investigation of pulmonary embolism, researchers of [180] use the Difference of Gaussians and visual words in CT lung images from University Hospitals of Geneva. They reported more than 60% of precision in the cases retrieved. In [64] images from PET images of Royal Prince Alfred Hospital are processed by 3D Gabor wavelet filter and authors aimed to analyze different dementia diseases such as Alzheimer, vascular dementia and frontotemporal dementia.

5. Indexing methods

For indexing features, we found the traditional vectors applied to 83% of the papers [181,70,182,28], while graphs represents 4% [30,120,171]. In the next sections, we detail graphs and k-d trees, since they are more complex structures that can provide an efficient way for storing features that must be quickly retrieved.

5.1. Graphs-based indexing methods

A possible solution for indexing features of an image is based on graphs, as shown in Definition 1 [183]. This indexing method has been employed since the image structure, as well as the characteristics extracted, have been increasingly complex. In the 3D domain for example, the information about the 3D object could be related to different aspects, such as volume, area, spatial distribution of voxels, and vertices. Thus, this largest range of options generates descriptors with more characteristics and manipulating this information can be easier using graphs [4].

In a graph, nodes and edges can be associated to attributes, called labels. In the 3D domain, we can use the vertices/voxels to represent the graph nodes and the edges as spatial relationship between the nodes, for example.

Definition 1. Let $V(g)$ the vertices set of a graph g and E(g) the edges set. A label function, l, maps a vertex or an edge to a label. The size of a graph is defined by the number of edges and denoted as $|g|$. The set of graphs g generating a graph G.

$G = \{g_1, g_2, \dots, g_n\}$;

$g = \{V_1(g), V_2(g), \dots, V_n(g), E_1(g), E_2(g), \dots, E_n(g)\}$

To compute the dissimilarity distance between graphs, optimized search techniques, such as bubble sort, hashing and matching functions are used [4]. Although these techniques are time-consuming, they present good accuracy.

An approach using graphs was applied in [32], which stored the lung tumors information (volume, indication of malignity, among others) in nodes, and their spatial distribution on PET scans images is represented by edges. The authors reported an average precision of 60%–70% in the exams retrieval based on the position of lung tumors and their structure information.

5.2. K-d trees

A K-*dimensional* tree (k-d tree) is a complex type of indexing structure, in which partitions of the data structure are in the n-*dimensional* space [4]. In the image retrieval domain, each image can be represented by a features vector, which can be high-dimensional. Thus, each feature vector is mapped into a k-d tree space, and the retrieval can be performed using specific algorithms, such as round-robin [183].

A k-d tree divides the features vector space into (*d-1*)-dimensional perpendicular hyperplanes to a specific coordinate axis. Every node has at least two children and the manner in which we structure the information can be customized [184]. We can, for example, specify a threshold value to detect whether a new features vector is a "child".

The nodes can be arranged according to some spatial information of the 3D models, as proposed in [147], which stores the information regarding curved shape of heart structures provided by MRI images in the nodes. The goal of the authors is to retrieve the medical slices most similar to the one given as query, ordering the database according to the slices similarity.

6. Similarity comparison methods

The technique used to compare the similarity among graphical objects is also a key factor in classification and retrieval. These techniques have influence in the final results, since they define how the objects must be compared, classified or clustered. In this context, some studies focus only on evaluating which similarity functions or classifiers best suit certain contexts [143,108,124].

Some techniques were most frequently used by authors for measuring similarity. We can mention, for example, distances of the L_p space (Definition 2), which were used in 32% of the papers such as Minkowski distances [185,186].

Definition 2. The distance of order p between any two points $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n) \in \mathbb{R}^n$ is defined by:

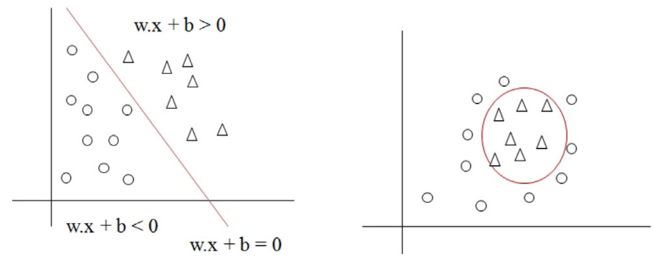
$$Distance_p = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p} \quad (4)$$

When p = 1, Manhattan Distance is defined, while p = 2, Euclidean Distance is defined and when p reaches infinity, we obtain the Chebyshev distance.

Machine Learning-based techniques are also commonly used in retrieval and classification methods. In this category, we can highlight the Support Vector Machine (SVM) and the K-Nearest Neighbor (KNN) implemented in 23% and 3% of the papers included, respectively [34,155].

SVM aims to generate dichotomies, i.e., separating n-dimensional data $(x_1, x_2, .., x_n)$ into well defined classes through at least one hyperplane. SVM can be classified as linear or non-linear. When there is a linear SVM, it is possible to split the set of data into separated groups. Classifiers that allow such division are illustrated in Fig. 6(a). They are defined by Eq. (5), where $w \cdot x$ is the scalar multiplication between vectors w and x, w is the normal vector in relation to the hyperplane and b is the bias [187,188]. Fig. 6(b) presents an example of non-linear SVM. In this approach, the data types cannot be separated by the linear approach. Thus, it is necessary to map the original data into a higher space using the inner product between any points of original data (x_i, x_j), as shown in Eq. (6).

$$y_i = \begin{cases} +1 & \text{if } w \cdot x_i + \mathrm{b} > 0, \\ -1 & \text{if } w \cdot x_i + \mathrm{b} < 0. \end{cases} \quad (5)$$



(a) Linear SVM (b) Non-Linear SVM

Fig. 6. SVM approaches: (a) represent a linear SVM; (b) represent a non-linear SVM.

$$K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j) \quad (6)$$

Approaches using SVM are often cited in the studies included. In [115] a SVM with radial basis function (RBF) kernel is used to detect abnormal shape and texture patterns in 2D brain MRI, and in [75] SVM with RBF kernel is applied to classify supraspinatus muscle disorders.

Finally, the KNN is one of the simplest methods in the Machine Learning area, which aims to determine whether a new element belongs to a specific class. It computes the distance between the new element and the elements previously classified. The group of elements with the shortest distance is chosen as the "owner" of the new element [4].

Regarding the application of these methods to similarity comparison between the feature vectors, both methods (Distances functions and Machine Learning) are equally applied between 2D and 3D object analysis. In both techniques for retrieval information (CBIR and classification), Artificial Intelligence (AI) techniques with the predominance of SVM are most used. They are present in 70% of the papers classified in the CBIR group and in 85% of the papers of the classification category. Some limitations noted concerning the application of AI techniques to compare the similarity among feature vectors are related mainly to the need of combining several parameters of the classifiers to optimize the result [68]. Additionally, as highlighted in [93], the need of new processing is frequent, since the SVM classifier training dataset must be recalculated for each new object introduced in the database.

7. Databases

An important challenge for studies related to medical images is how to obtain the necessary data to evaluate techniques. Besides the medical images themselves, information about specific diseases (medical reports, and indication of specific slices, for example) must to be obtained and this can make the evaluation of techniques a very difficult task. Thus, public medical images databases are very important, but their formation is not easy.

As aforementioned in Section 3, few included papers (28%) cited the medical image databases used for evaluating their approaches. Most of them worked with specific sets of images provided by partners (hospitals and medical experts). When the papers cited that the research used medical image databases, we verified a predominance of public databases such as ADNI [189], which provides brain MRI and PET images, and LIDC [177], which provides lung CT and Computed Radiography (CR) images. Table 6 presents all the public medical databases found and the respective studies where they were cited.

The databases presented in Table 6 are available for everyone and some of them contain cases of specific diseases (Alzheimer and Oncology problems, for example), specific human organs, and

Table 6
List of medical images databases used in the included papers.

Database	Description	Images modalities	Papers
Alzheimer's Disease Neuroimaging Initiative (ADNI)	Exams of Alzheimer's disease patients, mild cognitive impairment subjects and elderly controls.	MRI and PET images, genetics, cognitive tests, CSF and blood biomarkers	[126,39,65,40,66,190]
BrainWeb [191]	Set of realistic brain MRI data volumes produced by a MRI simulator, and images of Multi Sclerosis disease.	MRI images	[142,87,22,89,172]
Diabetic Retinopathy Database [192]	Benchmark of diabetic retinopathy detection from digital images.	Digital fundus camera	[99,114]
CLEF Cross Language Image Retrieval Track (ImageCLEF)[193]	Different images (generic and medical) for computational challenges to evaluate the best techniques for image retrieval task including segmentation, filtering and others image processing techniques.	MRI, CT, X-ray, CR, SPECT and PET	[109,174,165]
Image Retrieval in Medical Applications (IRMA)[194]	Focused on CBIR of radiographies.	X-ray	[140,153,165]
Lung Image Database Consortium (LIDC)[195]	Lung lesions.	CT	[45,34,111,31,157,19,182]
National Health and Nutrition Examination Survey (NHANES)[196]	Surveys into USA population health and habits besides medical exams.	MRI, CT, X-ray, PET and SPECT	[119,173]
OncoPet [197]	Distributed database of realistic simulated whole body PET images focused on Oncology.	PET images	[29]

specific image modalities (PET, MRI or CT). Some databases are more generic, but usually medical reports are not available, such as IRMA [194] and ImageClef [193], which hinder the evaluation of techniques and the comparison among different approaches. Another important database is the Cancer Imaging Archive [198] used in [199], which since 2014 groups several databases to help in cancer diagnosis through 2D and 3D object analysis. In this repository we can found images related to different organs and diseases such as breast, brain and prostate cancer.

8. Applications

The scenario of medical images classification and retrieval emphasizes different subjects. Techniques are applied to differentiate human organs, structures or diseases. Fig. 7 illustrates the distribution of the included papers. Some considerations about this distribution must be highlighted.

Firstly, brain and lung images are the most frequent subjects of study. Brains were analyzed in 48% , lung in 17% and heart in 21% of the included papers. More specifically, most of the papers aimed at identifying and/or classifying Alzheimer disease using MRI brain images, followed by detection of lung tumors. Both human body structures have public medical database available (LIDC and ADNI).

In addition to brain and lung images, we found several works dealing with heart, intestinal and bones structures. For heart images the most studied topic aims to analyze the heart structure as a whole. In [122], for example, the objective is to quantify global and regional left ventricular systolic function to discriminate segments showing an abnormal regional wall motion. The researchers used statistical shape modeling technique getting an area under a ROC curve of 0.87. In [46], the authors applied a set of shape descriptors (Regional Surface Changing, Global Surface Curvature, Surface Distance, Normalized surface distance, and Effective Radius) to quantify the left ventricle structure.

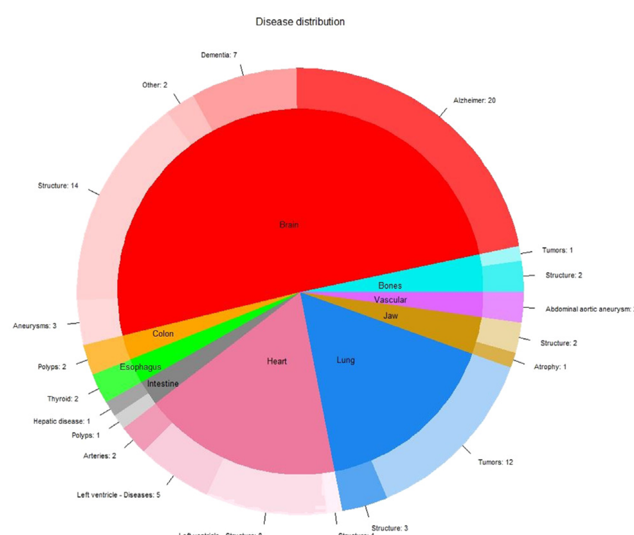


Fig. 7. Disease distribution per human body structure.

Related to intestinal medical images analysis, authors are focuses in disease classification and retrieval. An example is the study [200], which applies a texture descriptor based on gray level co-occurrence matrix to classify suspicious regions that present polyps. The authors achieved more than 75% of average accuracy, using a set of 20 patients exams.

A common problem investigated considering all types of images is the structure of the human organs. In this context, in [201] the

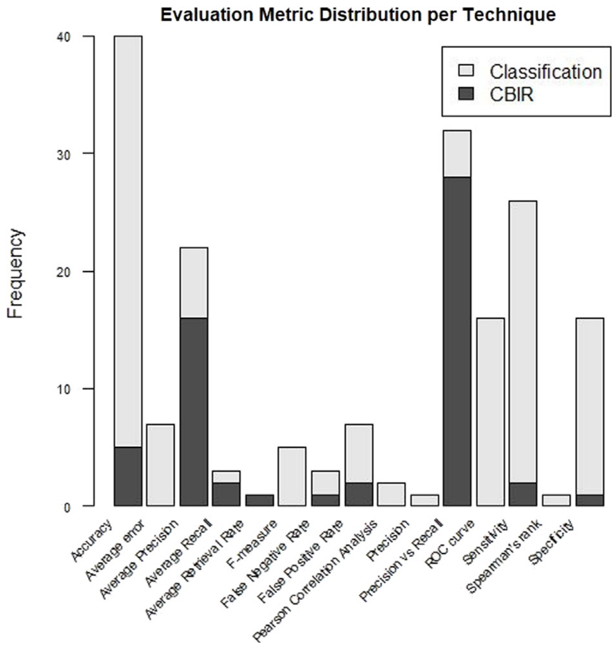


Fig. 8. Relationship between the evaluation metric analyzed in the included papers and their respective distribution per technique.

Table 7
Evaluation metrics cited in the studies included (TP: True Positive, FP: False Positive, TN: True Negative, TP: True Positive, d_i: distance between ranks, R: sum of the ranks, n: sample size, cov: covariance, σ: standard deviation).

Metric	Equation
Precision	$\frac{tp}{tp+fp}$
Recall or Sensitivity	$\frac{tp}{tp+fn}$
Accuracy	$\frac{tp+tn}{tp+fp+tn+fn}$
Specificity	$\frac{tp}{fp+tn}$
F-measure	$2 * \frac{Precision*Recall}{Precision+Recall}$
Spearman's rank	$1 - \frac{6\sum d_i^2}{n(n^2-1)}$
Mann–Whitney U test	$R_i - \frac{n_i(n_i+1)}{2}$
Pearson Correlation	$\frac{cov(X,Y)}{\sigma_x \sigma_y}$

authors analyze the topology of 3D vascular trees. In the same context, in [202] the lateral pterygoid muscle deformation is detected and quantified based on mandible MRI exams.

9. Evaluation metrics

Methods to evaluate and to compare techniques to store and to retrieve medical images are essential to validate the results found and to verify if the research hypotheses can be accepted or rejected. Fig. 8 shows an overview of the evaluation metrics and tests performed by the included papers. Table 7 presents a list of equations of the most frequent evaluation metrics found.

Accuracy is the most used among all the metrics (25% of the studies), mainly cited in papers of the classification category. In the studies in the CBIR category, Precision *vs.* Recall is the most widely used, presented in 51% of the papers. Considering the total of papers, Precision *vs.* Recall is present in 20%.

Another representative metric is specificity, used mainly in papers of the classification category, representing 15% of all the metrics. Finally, the ROC curve is also frequent in classification problems. Even though some papers used Specificity and Sensitivity metrics, most of researchers does not use these metrics to compose ROC curve, since we just found this metric in only 5% of the papers [45,116,120].

In addition to these metrics, we also found some non-parametric tests, such as Mann–Whitney and Spearman's rank [49,28], as well as parametric ones, such as Pearson Correlation [86], but they were not frequent enough to be presented in the graph of Fig. 8.

10. Discussion

From the data presented in the previous sections, the classification and retrieval of medical images can be observed to have increased over the years, producing numerous studies. Besides understanding which techniques are applied to which goals, we have to critically analyze this knowledge domain to identify the trends and challenges to be overcome.

In a general analysis, the following points were observed: in relation to the quality of included studies, the h5-index of the papers included is higher for Journals than for Conferences, and it is also higher for classification problem articles than for CBIR articles. There is a predominance of proprietary medical databases for tests as well as a great difficult in performing tests with a considerable number of cases. However, we found some papers working with a large set of images and 3D objects, mainly from lung and brain focused in cancer and dementia diagnosis, which can contribute to the greater interest in these knowledge fields. Public databases in these areas facilitate the techniques evaluation.

From the analysis conducted, advances are observed in classification retrieval of 3D medical objects and images. The gaps we identified in the literature analyzed can be explored as opportunities for new research lines, as described below.

10.1. General definitions

The first item to point out regards to the differentiation between CBIR and classification problems. In some studies authors state that classification can be associated to CBIR since a classifier can be applied to measure the similarity to improve the system accuracy [203]. However, the CBIR main goal remains: retrieving the most similar images to an image given as a query parameter, which can imply several images as a result. However, in our study, we found many papers focused only in the classification problem, without the concept of query by example and retrieval of similar images as a result. These papers only analyze how the images can be classified, usually using two classes: normal and abnormal cases. All these approaches are being considered in our mapping. Therefore, this is one of the challenges of the area: to standardize the nomenclature of these techniques both for avoiding misunderstanding and for finding related studies when a research is being conducted.

Fig. 4 shows an interesting behavior related to the amount of publications that considers medical or 3D object image processing: there is a decrement number of publications after 2014, but it is wrong to affirm that this knowledge domain is losing relevance. As shown in [204], this subject is very active research field and authors pointed out some future trends such as the application of multi-features to discriminate properly the image analyzed and the performance required for classification and retrieval process. Also, in [11] it is highlighted the "new era" of deep learning and how this concept is few applied mainly on CBIR domain, which opens up new opportunities in future coming. We observed that papers related to the utilization of deep learning in CBIR started on 2007 and was more disseminated after 2015, at 2017 we noted more than 66 papers dealing with deep learning techniques CBIR problems. However only in 2013 we found studies that applied this approach in medical images. In 2017, just 14 papers were published considering deep learning for CBIR applied in medical images and deep learning.[4] The result presented above indicates that deep learning and AI-based techniques " wave" are coming to the medical image domain and it is very plausible that in the next months/years we note a increment on this topic in the publications related to CBIR and classification.

Beyond the trends identified by [11], we analyzed several works on this Systematic Mapping and we did not find studies which deal with both 3D objects (reconstructed and set of slices). Consequently, it was not possible to verify if the time to process the queries and the efficiency were better for any specific approach. The evaluation of these two approaches, considering the same disease or structure, could allow different tests of time performance and retrieval systems efficiency. However, this type of evaluation requires descriptors development, similarity functions definition, as well suitable evaluation metrics for both 2D and 3D domains, besides techniques for processing both types of objects. This is not a trivial task, but could generate important results for the area.

10.2. Papers quality

We verified that it is usual for the same group of researches to have more than a paper with the same object of study, just changing one descriptor or a similarity comparison method for each paper. The evaluation method and the cases are usually the same. This hinders understanding the whole problem under investigation, since different papers can be in different databases and some of them may be missed. Additionally, partial results are usually published in scientific literature of smaller impact and the article is often not complete, which can result in an excluded paper in researches as the one presented here. Thus, publishing complete papers instead of prioritizing the number of publications is still a challenge to be overcome not only in this field of investigation, but in all research areas.

Papers that evaluated their techniques with experts were interestingly published in Journals and Conferences with high h5-index (average of h5-index equal to 35). This can be indicative that this type of evaluation can add value to the research. However, interdisciplinary research requires extra-efforts such as the proper involvement and commitment of all members of the research group in the project, establishing protocols and methods for evaluating the techniques developed. Moreover, the result found in this Systematic Mapping highlights the benefits of evaluation with experts: publications with greater relevance, more robust tests and more accurate evaluations. Also, this kind of questioning was discussed in [204] which pointed out the importance of bring the end-user to the final evaluation of CBIR systems.

10.3. Descriptors

The greatest advantage of processing objects in the 3D domain is the larger amount of information that they can provide, mainly related to the 3D object shape. However, it can be also the weakness of this approach, since not all the 3D representations have well defined geometry. In addition, the variety of rotation, translation and scale properties of 3D object requires preprocessing methods to align the 3D object or development of more complex descriptors to handle this variety. Also, the shape variety of specific diseases represents an additional challenge to implement a "standard" descriptor for 3D medical objects [4].

To deal with the time-consuming problem related to 2D slices, several techniques have been developed aiming to extract distinctive information from several slices, mainly associated to the shape and texture of the entire 3D medical object. In spite of this approach has several studies with good results, some limitations persist, such as the need of defining a Region of Interest (ROI), the need of techniques to apply shape, texture or color descriptors to different image resolutions, parametrization to run segmentation techniques and problems related to slices alignment, which may influence the results [132,135,165,140,143,148,93,155]. In this knowledge domain, the 3D texture descriptor is pretty much used and the work of [206] performed a good review of the literature focused on 3D solid texture in medical images.

Still about descriptors, this Systematic Mapping not covered semantic descriptors which is a relevant sub-domain of classification and retrieval techniques. This type of descriptor labels the 2D images and 3D object regions accordingly to the innate humans visual understanding about this region. In 3D domain this type of descriptor is used connected with several AI-based techniques such as neural networks, and SVMs [11].

10.4. Indexing methods

As mentioned in Section 3, we noted a predominance of traditional vectors during the features indexing. However, other indexing structures such as graphs and K-d trees are offering promising results.

The authors that used these alternative data structures point out that the biggest advantage is due to the possibility of offering, in addition to the features characteristics organization and indexing, the spatial information about the region where these features were extracted and, in some cases, how each feature is associated to each other [30,120].

Besides these data structures give more possibilities related to the features data organization, they offer new methods to compute the dissimilarity between them such as flow-based dissimilarity methods (min-cut and maximum flow, for example) and neural networks [207] .

10.5. Similarity comparison

Minkowski distance was the most used similarity function analyzed the included papers, followed by SVM technique. This information is coherent due to the fact that the most used indexing methods was traditional vectors and Minkowski distance is very common function used to compare this type of data structure.

However we noted some limitation in both approaches. The first one, related to Minkowski distance, is based on the fact that this technique is noise-sensitive, i.e, if the features vector has outliers in some features, this information will impact negatively the results. Additionally it is not possible extract local information from the similarity result (unless you divide the features vectors in small pieces associated to different regions of the 3D object analyzed).

Regarding SVM, the main limitation is the fact of this technique demands several parametrizations and a training dataset, normally the research that used this approach performs the algorithm evaluation in a very controlled scenario. When the system receives

[4] This search considered the IEEE Xplore Library [205].

a different input: new disease to be investigated or images from different body structures, the system needs a complete new set of adjustments. This frequent changes on the parametrization is the major disadvantage of this approach.

10.6. Databases

We verified that more than 70% of the included papers did not report the source of medical images they used. We cannot conclude if this is miss information during the methodology description or if the medical images are from particular databases, since we noted a strong relationship between Medical Schools and Computer Science research groups.

However, we noted there are important public databases, as mentioned in Section 7, such as LUNG Image Database [195], ADNI [189] and Cancer Imaging Archive [198], which provide a larger number of different types of medical images examinations for different diseases. Coincidentally, as we noted in Section 8, the most diseases investigated in the included papers belongs to one of these public databases.

Despite not being a determinant factor to increase the researches in the area, this could favor the evaluation of the techniques as well as the comparison of results with those obtained by other researches.

10.7. Applications

We did not find a relationship between the computational technique (CBIR, classification) and specific parts of the human body or a specific disease. All these categories are equally distributed in the selected papers. Yet we found a relationship between the some diseases, such as Alzheimer and Lung tumors and the development of texture descriptors for 2D slices. As it is known, these diseases are investigated mainly through CT examinations, which generate slices with high resolution and very detailed images about these body structures. Thus, researches of this expertise, identified that texture descriptors are being efficient to identify the diseases patterns on those images, since it can be found analyzing the homogeneity, coarseness and granularity of the region.

In our study, we also investigated information about the adherence of the industry to the techniques for medical image classification and retrieval. We also noted only few papers reporting that the techniques were applied in clinical routine. Our hypothesis is firstly related to the difficulty in approving computational systems to be used in daily Healthcare routine or turn them into commercial products. Secondly, the absence of this type of information in the studies can be related to privacy restrictions, but the papers do not mention that. Finally, the authors may still be dealing with technical problems, such as the need to improve their techniques, involving parametrization dependent on medical images sets, ROIs extraction, spatial and contrast resolutions.

These questions can generate non-intuitive systems, which are difficult for health experts to use. However, it is worth highlighting that in many papers we found this aspiration — the method being applied to clinical daily routine as "future work". We believe that through a development of protocols, pilot studies and support of business incubators, this goal have some advances in this scenario in the next years.

In the mean time, we are observing the advances in medical images modalities, such as MRI, CT, PET, SPECT and Ultrasound. Thus, a possibility for research is changing our mindset about the design of systems to aid the diagnosis, which should be an intelligent information provider in the machine while performing the image acquisition. This approach favors the development of embedded systems and some companies have heavily spent resources in this direction [2].

10.8. Evaluation metrics

For evaluation metrics we verified that Precision *vs.* Recall is the most used metric for evaluation of CBIR systems and accuracy for classification studies. These metrics are very consolidated on this knowledge domain and could provide a good evaluation related to the techniques performance.

However, if we consider the clinicians' evaluation of these techniques developed, we noted only few papers reporting it, as mentioned in Section 3. This raises a question: why? Time and schedule problems of clinicians? Evaluation with health professionals is not considered important by the researchers who developed the techniques?

We believe that it is a problem related to synergy between the two different groups (health experts and designers) than a wrong impression that is not important the clinicians evaluation. It is clear for us, based on the paper quality information, that authors that provide results with both evaluation (traditional metrics and clinicians evaluation) publish the results in more qualified scientific literature.

10.9. Opportunities

In summary, the main challenges and opportunities in this field can be briefly listed as follows:

- optimizing the parametrization and indexing methods to provide faster search/classification. This includes developing methods with less parametrization needs and indexing methods suitable to problems dealing with local and global characteristics;
- understanding the anatomy of human organs as well as their deformation due to a specific disease, and designing suitable descriptors to aid the diagnosis. Shape and texture descriptors have a great potential for clinical problems. We have a good number of diseases that cause shape deformation in the some organ structures. Anomalies, such as aneurysm, infarction, and even tumors can be analyzed as benign and malignant based on their shape. Other diseases, such as Alzheimer, do not cause shapes deformation but visually we note different patterns on the examinations, which can be differentiated through texture descriptors.
- exploring the local perspective of descriptors in the 3D domain. Global and local descriptors have their own advantages and disadvantages, mainly related to noise sensitivity. From our perspective, descriptors that act locally and, at the same time, support some noise in the information, perform well in several problems. This kind of technique is still underexplored in 3D medical objects and images classification and retrieval.
- developing or improvement of comparison methods are directly related to system performance, and we noted that AI-based methods are being used more extensively in the last years. Besides these techniques improve the system efficiency, we noted a common concern about the amount of parametrization and the necessity of training datasets to adjust properly those techniques. In addition, as we previously discussed, these several adjustments could impact on the system utilization by end-users. Thus, it is very welcome researches to deal with optimization or automation of these parameters.
- developing new indexing methods we note a predominance of traditional vectors in the included paper. Despite this, some authors identified that others structures can be a good as an alternative, such as graphs and k-d trees. Thus, it is important and an opportunity, mainly for 3D domain that provides a

large amount of information. Testing and validating alternative indexing structures could improve the systems performance.
- improving medical databases availability, which is crucial for comparing the techniques;
- conducting studies for develop methodologies to improve the synergy between research groups, aimed to reach end-to-end evaluation both for computational and end-user perspectives.

11. Conclusion

This Systematic Mapping aimed to provide a general overview of studies aimed to classify and to retrieve medical 3D objects, besides a critical view about some aspects of these papers. We noted a growing development of methods for 3D objects, but many of them are adaptations of techniques from the 2D domain, for both descriptors and methods for similarity comparison and evaluation. Therefore, we concluded that specific descriptors and specific evaluation methods for the 3D domain are still a gap to be covered in this area.

We also found few public databases, with limited scope concerning diseases represented in the medical images as well as modalities included in the database. The establishment of researchers networks aiming at forming public databases with enough information to allow complete evaluations of techniques constitute an opportunity still underexplored in the literature.

The low adherence of health professionals – or the lack of this information in the papers included – indicates that another opportunity is gathering researches aiming at developing new processes to transfer technology to the industry.

This study aimed to answer some questions, presented in Section 1. Some of them were answered along the paper, but we would like to highlight those more specific here:

1. are the researchers producing relevant studies in this area? Yes. As discussed in Section 3, most of the 107 papers included were published in periodicals and conferences with high h5-index;
2. where the researchers are publishing? As mentioned in Section 3, the publication are divided almost equally between conference and journals. Both conferences and journals present high impact;
3. has the Healthcare area really benefited from the classification and retrieval knowledge field? Yes. Although only few studies reported applying the techniques developed into daily medical routine (we pointed out some reasons in Section 10) we noted a strong partnership between Medical Schools and research groups (since many experiments were made with images provided by internal collaboration and not by public medical databases, as discussed in Section 7). This can indicates the interest of both areas in the research.

Finally, we highlight the importance of this area for the next years, as complex data and information will be more explored and Healthcare is considered a mainstream sector to be benefit from that. Therefore, this mapping intends to provide a contribution to help present and future researchers to quickly locate general information about this topic.

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