Flexible Retrieval of X-Ray Images Based on Shape Descriptors Using a Fuzzy Object-Relational Database

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Abstract — *This paper presents a novel approach for medical image storage using a Fuzzy Object-Relational Database Management System (FORDBMS). The system stores medical images along with a set of parameters describing their content. Flexible queries can be performed over these parameters to retrieve images matching visually. To illustrate the capabilities of the FORDBMS, parameter curves are obtained from X-Ray images of patients suffering from scoliosis, and queries are performed when looking for images with a determined curve pattern. Results show that retrieved images visually match the condition established in the query.*

Keywords — Image Retrieval, Fuzzy Databases

1 Introduction

Images are a fundamental tool in health care for diagnosis, clinical studies, research and learning. Currently, there are multiple techniques to capture images from patients to help diagnostic tasks such as X-Ray images, Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Ultrasonography, etc. The diagnostic task generates a large amount of images which must be archived for future evaluations. Fortunately, most of these techniques produce digital images, which are more efficiently archived and handled through computer systems than physical ones. In medical imaging, these computer systems are called Picture Archiving and Communication Systems (PACS). PACS are computers or networks devoted to the storage, retrieval, distribution and presentation of images. These systems solve the problem of storaging digital images but do not provide mechanisms to retrieve them based on their content.

Content-Based image retrieval (CBIR) [1] is the application of computer vision techniques to the problem of digital image search in large databases. First image retrieval approaches were based on captions and textual descriptors collected by humans. Nowadays, image retrieval systems improve the textual-based ones using features such as color, texture or shape, which are automatically extracted from images [2]. In this regard, a very important point to take into account is the imprecision in the feature descriptions, as well as the storage and retrieval of that imprecise data. To deal with this vagueness, some interesting approaches introduce the use of fuzzy logic in the feature representation, as well as in the retrieval process [3, 4, 5]. These fuzzy approaches also allow to perform queries on the basis of linguistic terms, avoiding one of the drawbacks of the classical image retrieval systems, where the queries have to be defined on the basis of images or sketches similar to the one we are searching for.

Database Management Systems (DBMS) are crucial in CBIR for retrieval purposes and, as we have explained above, these systems must be able to represent fuzzy data as complex datatype structures to provide flexible content based retrieval. There is a wide variety of proposals for fuzzy data handling in databases [6, 7, 8, 9, 10, 11] but in general these models and/or implementations do not have enough modeling power and performance for image indexing applications. For these kind of applications we propose to use the Fuzzy Object-Relational Database System (FORDBMS) model introduced in [12, 13]. This model evolves classical fuzzy databases models to incorporate object-oriented features for a powerful representation and handling of data, fuzzy or not.

CBIR techniques get more semantical results when applied to a specific domain or application area, as knowledge on the domain and on the image characteristics helps the process to extract the relevant features for this specific area of application. Health care is an application area that may benefit from the CBIR techniques. If we focus the CBIR techniques on the analysis of a certain pathology we can get high level features processing certain types of images. For example, there are some proposals to extract vertebral and spinal shapes from X-rays [14, 15] (these algorithms need some user intervention). The paper [16] describes a technique to automatically measure Cobb angle [17] for scoliosis pathologies given the end vertebras of the curve.

This paper shows how our FORDBMS is suitable for easy image representation and retrieval, using the fuzzy descriptors obtained by means of computer vision algorithms [18] or provided by experts. To illustrate this, we show the process to represent a structure in the FORDBMS describing scoliosis measures (Cobb angles) obtained from anteroposterior X-rays. Aditionally, we will show that the use of fuzzy comparators implemented by the FORDBMS in queries let us retrieve images that match the expected visual characteristics searched.

The rest of the paper is organized as follows. Section 2 describes the scoliosis pathology and the use of X-rays for its diagnosis. Section 3 introduces the fuzzy object-relational database system used to store and retrieve the fuzzy data. Examples of queries are presented in Section 4 and, finally, the main conclusions and future works are summarized in Section 5.

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2 Idiopathic scoliosis and its X-ray based diagnosis

In order to show how the use of fuzzy databases can help in health care, we have focused on the study of representation and retrieval of images related with idiopathic scoliosis. In this section we will describe the most relevant characteristics of this pathology in relation with our purpose.

Scoliosis is a three-dimensional deformation of the spine that produces vertebral rotation and crushing, and lateral curvature. It is typically classified as congenital (caused by vertebral anomalies present at birth), idiopathic (sub-classified as infantile, juvenile, adolescent, or adult according to when onset occurred) or as having developed as a secondary symptom of another condition, such as cerebral palsy, spinal muscular atrophy or due to physical trauma. Depending on the severity and progression of the deformation may be necessary treatment, consisting of observation, orthotic (brace) treatment, or surgery. About 2-4% of the adolescent population has some degree of scoliosis. Approximately 2.2% of these adolescents will require treatment.

To diagnose and treat scoliosis it is necessary to perform measures of the spine deformity. There are physical examinations to initially detect the presence of the deformity, but a precise diagnosis and treatment needs the help of radiologic techniques. The most accurate technique to measure spinal deformity is Computed Tomography (CT), that provides a three-dimensional view of the spine. However this technique is expensive and exposes the patient to a high radiation. Taking into account that a patient having scoliosis may need observation and treatment for many years and many radiologic tests, the frequent use of this technique may be inappropriate. X-Rays expose the patient to a lower radiation and, because of this, full-length standing spine X-rays are the standard method for evaluating the severity and progression of the scoliosis. Anteroposterior X-rays (AP X-rays) project spinal deformities as curves. The standard method to quantitatively asses curvatures is the measurement of the Cobb angle on AP X-rays. The Cobb angle [17] can be manually measured by calculating the angle between the lines respectively drawn along the upper endplate of the superior end-vertebra and the lower endplate of the inferior end-vertebra, as shown in Fig. 1. Using this measure each curve present in the spine is characterized by means of four parameters: the side of the convexity of the curve (right or left), the superior end-vertebra, the inferior end-vertebra and the angle value. It is important also to identify the apical vertebra associated with the adjacent disc interspaces that have the greatest segmental angulation of all interspaces in the curve. This vertebra occurs at the horizon or apex of a curve (T9 in Fig. 1).

The manual measurement of Cobb angle depends on experience and personal judgment. Errors are due to selecting different end- vertebrae and estimating different slopes of the vertebrae. The standard measurement error is 3° to 5° for the same observer and 5° to 7° for different observers.

The use of AP X-rays is useful for diagnosis, clinical studies and health learning. To help these purposes, it will be interesting to perform storage and retrieval of X-rays from a database based on curves parameters present in the spine. The problem is that, as we have shown, measures are imprecise and the query parameters needs to be flexible. For this reason, classical databases are not suitable for this purpose. It is necessary a Database System that can store imprecise data and can perform flexible queries on them. Moreover, as spine parameter description is complex, the database system must handle complex structures to represent imprecise data and must provide flexible comparators on these structures. Our FORDBMS, as we will show in next sections, have those capabilities.

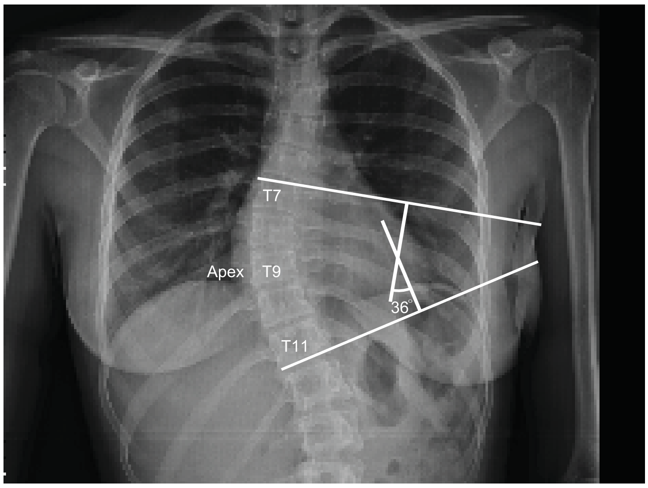

Figure 1: Cobb angle measurement.

3 The fuzzy object-relational database system

The recent proliferation of large image databases leads to the need for DBMS applied to multimedia libraries management to ensure high performance, scalability, availability with fault tolerance and distribution.

Nowadays, market leader DBMSs offer these required features transparently. However, the database models implemented by them, generally the relational model, are not suitable to manage fuzzy data, which is necessary for this kind of image description algorithms. In order to solve this drawback, some database models and DBMSs implementing them have been proposed. Nevertheless, the existing fuzzy DBMSs are in general research prototypes which do not match the high performance and other necessary requirements for this kind of applications.

In [12, 13] we introduce the strategy of implementation of our FORDMS model, that it is based on the extension of a market leader RDBMS (Oracle®) by using its advanced object-relational features. This strategy let us take full advantage of the host RDBMS features (high performance, scalability, etc.) and the ability for representing and handling fuzzy data provided by our extension, making this FORDBMS suitable to support systems for flexible content based retrieval of images.

3.1 Fuzzy datatype support

Our FORDBMS is able to handle and represent a wide variety of fuzzy datatypes, which allows to model any sort of fuzzy data easily. These types of fuzzy data, which are represented as classes with light gray background color in Fig. 2, are the following:

- Atomic fuzzy types (AFT), represented as possibility distributions over ordered (OAFT) or non ordered (NOAFT)

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domains.

- Fuzzy collections (FC), represented as fuzzy sets of objects with conjunctive (CFC) or disjunctive (DFC) semantics.
- Fuzzy objects (FO), whose attribute types could be crisp or fuzzy, and where each attribute is associated with a degree to weigh its importance in object comparison.

All fuzzy types define a Fuzzy Equal operator (FEQ) that computes the degree of fuzzy equality for each pair of instances. Each fuzzy datatype has its own implementation of this operator in accordance with its nature. Moreover, the FORDBMS provides parameters to adjust the fuzzy equality computation to the semantics of the data handled. For OAFTs the system implements other fuzzy comparators as FGT (fuzzy greater than), FLT (fuzzy less than), etc.

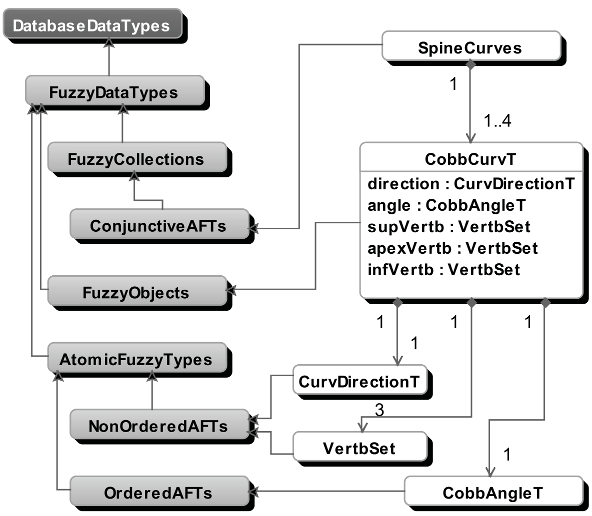

Figure 2: UML Class Diagram for Fuzzy types and SpineCurves Datatype.

3.2 Fuzzy datatype operators

Our FORDBMS can handle flexible comparisons over several types of fuzzy datatypes. Moreover, our system provides the possibility of adapting the behavior of some operators to adjust flexible comparisons to the semantics of the data modeled. The current section describes the most significant operators for the defined fuzzy datatypes, and their adaptation to handle flexible queries on complex objects like the spine curve description structure illustrated in this paper.

3.2.1 Fuzzy inclusion operator

The operator `FInclusion(A,B)` calculates the inclusion degree $A \subseteq B$, where A and B are instances of CFC. The calculus is done using a modification of the *Resemblance Driven Inclusion Degree* introduced in [19], which computes the inclusion degree of two fuzzy sets whose elements are imprecise.

Definition 1 (Resemblance Driven Inclusion Degree). *Let A and B be two fuzzy sets defined over a finite reference universe $\mathscr{U}$, μ_A and μ_B the membership functions of these fuzzy sets, S the resemblance relation defined over the elements of $\mathscr{U}$, $\otimes$ be a t-norm, and I an implication operator. The inclusion degree of A in B driven by the resemblance relation S is calculated as follows:*

$$\Theta_S(B|A) = \min_{x \in \mathscr{U}} \max_{y \in \mathscr{U}} \theta_{A,B,S}(x,y) \tag{1}$$

where

$$\theta_{A,B,S}(x,y) = \otimes(I(\mu_A(x), \mu_B(y)), \mu_S(x,y)) \tag{2}$$

We propose a modification that substitutes the minimum aggregation operator in equation 1 by a weighted mean aggregation operator, whose weight values are the membership degrees in A of the elements of $\mathscr{U}$, divided by the cardinal of A. This modification is made in order to obtain a less extreme resemblance inclusion degree, since it takes into account the importance of each included element. The *Modified Resemblance Inclusion Degree* is defined in equation 3.

$$\Theta_S(B|A) = \sum_{x \in \mathscr{U}} \frac{\mu_A(x)}{|A|} \cdot \max_{y \in \mathscr{U}} \theta_{A,B,S}(x,y) \tag{3}$$

with $|A| = \sum_{x \in \mathscr{U}} \mu_A(x)$. Our implementation of `FInclusion(A,B)` uses the minimum as t-norm, and the Gödel implication as the implication operator.

3.2.2 Fuzzy equality Operator

The operator `FEQ(A,B)` calculates the resemblance degree between two instances of a fuzzy datatype.

When `A` and `B` are two instances of CFC, this resemblance degree is calculated by means of the *Generalized Resemblance between Fuzzy Sets* proposed in [19], which is based on the concept of double inclusion.

Definition 2 *(Generalized resemblance between fuzzy sets). Let A and B be two fuzzy sets defined over a finite reference universe $\mathscr{U}$, over which a resemblance relation S is defined, and $\otimes$ be a t-norm. The generalized resemblance degree between A and B restricted by $\otimes$ is calculated by means of the following formulation:*

$$\beta_{S,\otimes}(A,B) = \otimes(\Theta_S(B|A), \Theta_S(A|B)) \tag{4}$$

Therefore, the implementation of the operator `FEQ(A,B)`, when A and B are instances of CFC, aggregates the results of `FInclusion(A,B)` and `FInclusion(B, A)` using a minimum t-norm.

If the operator `FEQ(A,B)` is applied when `A` and `B` are instances of the class *FO*, then, for the sake of flexibility, the resemblance degree between these objects is calculated as a weighted average of the resemblance degree of their attribute values. In the FORDBMS catalog we store some parameters for the attributes that belong to each fuzzy object. Specifically, the table *SDS_FO_ATTRIBUTES* stores into the column *relevance*, the relevance value of the considered attribute. This value attaches a weight to the attribute for the calculation of the `FEQ` operator. Moreover, if this value is set to -1 for an attribute, this attribute acts as determinant in the object comparison, in the way that, if the resemblance operator on this

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attribute returns 0, then the complete objects comparison returns 0. This parameter is useful, for example, in the case that we are searching for *"left curves"*, setting *Direction* attribute to -1, the query never retrieves a *"right curve"* even if resemblance for other object attributes is greater than 0. Another parameter that modifies the computation of the operator `FEQ` on fuzzy objects is the minimum percentage of attributes comparison greater than 0 (*min_pct*). This parameter, stored in the catalog table *SDS_FO_TYPES*, set the necessary number of attributes comparisons greater than 0 to get a value greater than 0 for the whole object comparison.

The following definition formalizes the ideas exposed above.

Definition 3 *(Parameterized Object Resemblance Degree). Let o_1 and o_2 be two objects of the class C, $obj.a_i$ the value of the i-th attribute of the object obj, $rel(a_i)$, relevance degree of the i-th attribute of the object obj, n the number of attributes defined in the class C, min_pct the necessary minimum percentage of attributes comparison greater than 0, and FEQ the resemblance operator.*

$$OR(o_1, o_2) = \begin{cases} 0 \text{ if} \\ (\exists i \in \mathcal{A} : FEQ(o1.a_i, o2.a_i) = 0 \wedge rel(a_i) = -1) \vee \\ (|\{a_i : i \in \mathcal{A} \wedge FEQ(o1.a_i, o2.a_i) > 0\}| < n.min\_pct) \\ \\ \sum_{i \in \mathcal{A}}^{n} FEQ(o1.a_i, o2.a_i).|rel(a_i)| / \sum_{i \in \mathcal{A}}^{n} |rel(a_i)| \\ \text{otherwise} \end{cases} \quad (5)$$

Our FORDBMS also let us relax the resemblance operator `FEQ` applied on *OAFT* values. To do this, the user must use the static method `relax(kernel_pct,support_pct)`, where `kernel_pct` sets the percentage that the kernel increases for each pair of values being compared, and `support_pct` sets the percentage increase for the support of these values.

4 Retrieving X-Ray images from database using its fuzzy description

Our FORDBMS can handle complex fuzzy data structures to represent rich semantic problems. It can store instances of these structures and provides a powerful set of operators to retrieve data based on flexible parameters. We have chosen an example based on the representation of the characteristics of the spine curves taken from AP X-rays to illustrate how flexible queries can retrieve interesting results for the specialists. Let us show how to model the data structure of this example on our FORDBMS, then we will perform some queries and we will analyze the retrieved results.

4.1 Database modeling for spine curve description

Our FORDBMS is capable of representing curves structures present in the spine measured from AP X-Rays, taking into account that the measures can be imprecise due to errors. It also provides parameters to adjust the fuzzy comparators used to get good query results.

The classes whose background color is white in Fig. 2 integrate the datatype structure of the database that represents spine parameters. As this figure illustrates, we model the curve description of the spine as a fuzzy conjunctive collection datatype (*SpineCurves*) which includes up to four fuzzy object datatypes (*CobbCurveT*). *CobbCurveT* datatype represents a spine curve measure. This datatype has five attributes: *Direction*, *Angle*, *SupVertb*, *ApexVertb* and *InfVertb* that store: the side of the convexity of the curve (right or left), the angle measure and, the superior, apical and inferior vertebra of the curve, respectively. Attribute *Direction* is of NOAFT type, this allows to perform queries with a not determined value for the side of convexity of the curve. The attributes *SupVertb*, *ApexVertb* and *InfVertb* store values of type NOAFT. The domain of this attributes (*vertbSetT*) includes 24 vertebrae that are enumerated as follows: $v_1 = L5, v_2 = L4, v_3 = L3, v_4 = L2, v_5 = L1, v_6 = T12, v_7 = T11, v_8 = T10, v_9 = T9, v_{10} = T8, v_{11} = T7, v_{12} = T6, v_{13} = T5, v_{14} = T4, v_{15} = T3, v_{16} = T2, v_{17} = T1, v_{18} = C7, v_{19} = C6, v_{20} = C5, v_{21} = C4, v_{22} = C3, v_{23} = C2, v_{24} = C1$. We will define a nearness relation on this underlined domain to take into account the adjacency between each pair of vertebrae as follows:

$$\forall i, j \in Cardinal(VertbSett) :$$
$$nearness(v_i, v_j) = \begin{cases} 1 & if\ i = j \vee i = j+1 \vee \\ & i = j-1 \\ 0.66 & if\ i = j+2 \vee i = j-2 \\ 0.33 & if\ i = j+3 \vee i = j-3 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The attribute *Angle* is of type OAFT, so we can store on this attribute numerical values, crisp or fuzzy (using a trapezoidal membership function). Measures obtained with errors for the angle can be represented as a fuzzy value for the attribute. This attribute allows flexible comparisons also. We can use the method `relax` described in the previous section on this attribute.

Once we have defined the type structure for the spine description, we can create a table that stores X-rays images together with their fuzzy descriptions as follows:

```
create table APXRay (
 image# number, xray bfile, SpineDescription SpineCurves);
```

We have inserted twenty images with their curve description to illustrate query examples; the statement for one image insertion is like this:

```
Insert into apxray values (
 313701 ,BFILENAME('APXRays','313701.gif'),
 SpineCurves(
     1,cobbCurvT(
        CurvDirectionT('RIGHT'),
        CobbAngleT(trapezoid(10.1)),
        VertbSetT('T2'),
        VertbSetT('T5'),
        VertbSetT('T10')
             ),
     1,cobbCurvT(
        CurvDirectionT('LEFT'),
        CobbAngleT(trapezoid(16.5)),
        VertbSetT('T9'),
        VertbSetT('T12'),
        VertbSetT('L2')
             ),
     1,cobbCurvT(
        CurvDirectionT('RIGHT'),
        CobbAngleT(trapezoid(12.5)),
        VertbSetT('L2'),
        VertbSetT('L4'),
        VertbSetT('L5')
             )
  )
);
```

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4.2 *Examples of Queries*

In this section we will illustrate some capabilities by performing a query that uses the `FInclusion` operator and a second one that uses the `FEQ` operator on `CFC` datatypes. To get flexible results on queries that involve whole fuzzy object comparison, it is advisable to relax comparison on angle attribute. To perform it we invoke the static method `relax` described in Section 3.2.2. In this case we relax 40% the kernel and 70% the support. This is the SQL sentence: `Execute CobbAngleT.relax(0.4,0.7);`

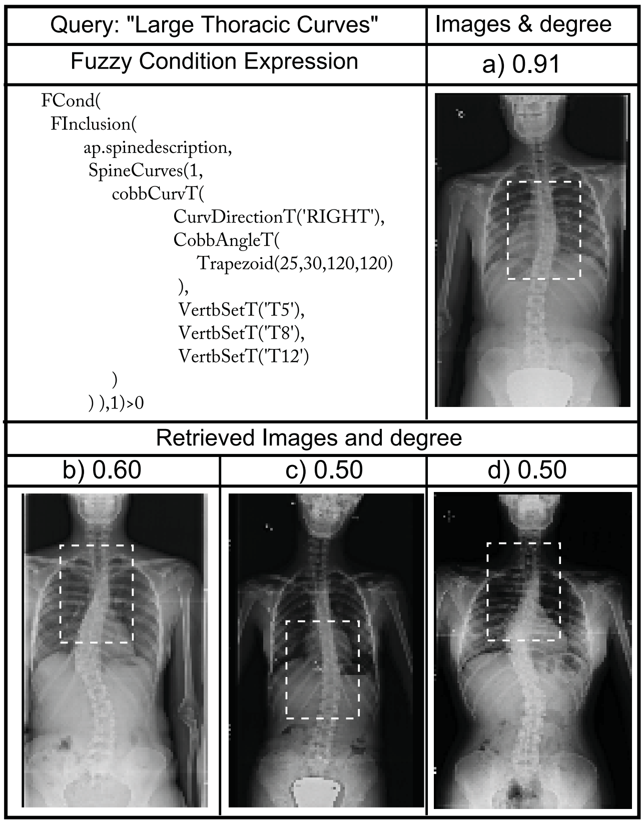

Figure 3: Searching images that include a thoracic pattern curve.

As shown in Fig. 3, we can perform queries that search images including a determined pattern of curves. In the example we illustrate the following query: *"Show X-Ray images and its compliance degree that include a large thoracic curve"*. The "thoracic curve" pattern proposed in [20] is described by the following approximate parameters: the convexity of the curve is on the right side, the superior end-vertebra is between T4 and T6, the apex vertebra is between T8 and T9 and, the inferior end-vertebra is between T11 and L2. The Fuzzy Condition Expression cell of the Fig. 3 shows the parameters used for the `WHERE` clause of the query statement, where the concept "large" is modeled as a trapezoidal distribution that matches Cobb angles that are approximately greater or equal than 25-30 degrees.

To perform the query we use the `FInclusion` operator, described in Section 3.2.1, which evaluates the similarity of the queried curve with respect to each curve included in the spine description. The query retrieves four images from the database. The image a), includes a curve, highlighted with a rectangular area, witch takes the values 'Right', 21.8, T5, T8, T10 for the parameters: orientation, angle size, superior, apex and inferior vertebrae, respectively. The compliance degree for this image with respect the query is 0.91. As we can see, this image includes a curve that appreciably matches the concept "large thoracic curve", this is the reason for the high degree computed. Visually, the marked curve in image b) weakly matches the concept "thoracic curve", this is the reason for a minor compliance degree. Image c) includes a curve that tends to a "thoracolumbar curve" concept; because of this, the retrieved compliance degree is low, 0.5. Finally, image d) includes a curve that tends to a "cervicothoracic curve" concept, the compliance degree (0.50) confirms this fact.

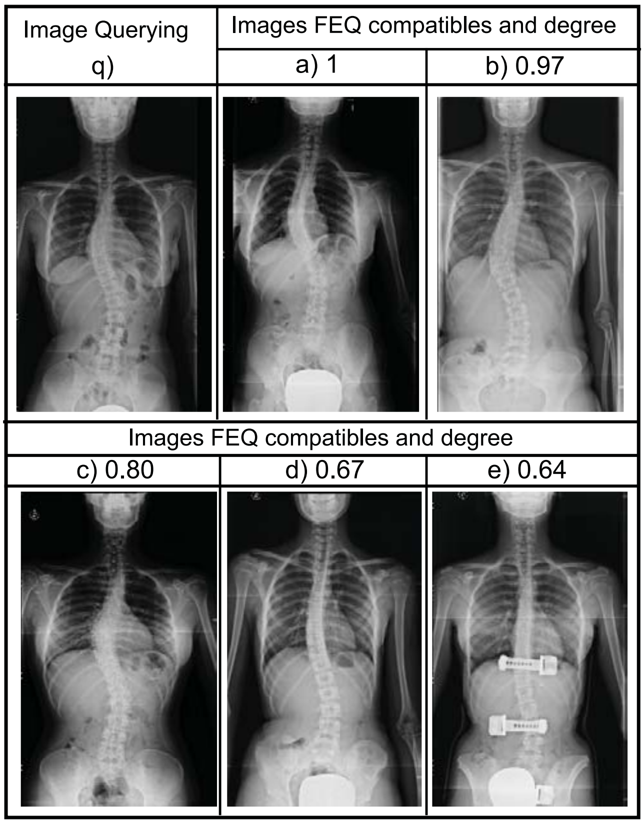

Figure 4: Searching images that present similar spine curvature that image q).

In some studies it may be interesting to find X-rays of patients that present a similar curve pattern to a given one. In our database, we model these curve patterns present in the spine as a *CFC*. To find similar curve patterns, our FORDBMS provides the operator `FEQ` which operates on *CFC* as has been described in Section 3.2.2. The query shown in Fig. 4 searches for X-rays of patients presenting similar curve patterns that the image query q). The SQL syntax is:

```
SELECT ap1.image#,ap1.xray,ap1.cdeg(1)
FROM apxray ap1, apxray ap2
WHERE ap1.image='q'
     AND FCOND(
         FEQ(ap1.spinedescription, ap2.spinedescription),1
        )>0 order by cdeg(1) desc;
```

As can be seen, higher compliance degree for an image denotes better visual matching with the queried image. Another interesting aspect of our results is the following: the images retrieved by the two kinds of queries evaluated hold that, the

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lower is the curve pattern matching, the lower the compliance degree computed for these one is.

5 Concluding remarks and future work

This paper shows that a FORDBMS is a powerful tool to represent flexible descriptors obtained from images by means of computer vision algorithms or provided by experts. The system also provides parameterized fuzzy comparators to retrieve images based on those descriptors in a flexible way. To the best of our knowledge, there is no system for flexible image retrieval that provides same capabilities on the subject considered in this paper. The prototype of FORDBMS used to show these results are implemented on the RDBMS Oracle® 10.2. Thereon, it is interesting to make the following remarks:

- The prototype has not implemented yet any index technique to accelerate the data retrieval based on fuzzy conditions. For this reason, the queries shown have been computed by means of a sequential search; moreover, the complex fuzzy datatype structure used for the spine curve representation more decreases the efficiency if none index technique is used. We are working on the implementation of the indexes techniques for fuzzy data proposed in [21, 22]; this will provide us mechanisms to optimize retrieval process.
- The scalability of our FORDBMS and CBIR system shown is guaranteed by the scalability of the host ORDBMS system, Oracle® 10.2.

Future work will involve too the enrichment of fuzzy features of the FORDBMS to enhance support for image content based retrieval. Finally we will study another application domains to perform content based retrieval using our FORDBMS.

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