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Semantics-driven Annotation of Patient-Specific 3D Data: A Step to Assist Diagnosis and Treatment of Rheumatoid Arthritis

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Abstract In the digital era, patient-specific 3D models (3D-PSMs) are becoming increasingly relevant in computer-assisted diagnosis, surgery training on digital models, or implant design. While advanced imaging and reconstruction techniques can create accurate and detailed 3D models of patients' anatomy, software tools able to exploit fully the potential of 3D-PSMs are still far from being satisfactory. In particular, there is still a lack of integrated approaches for extracting, coding, sharing and retrieving medically-relevant information from 3D-PSMs and use it concretely as a support to diagnosis and treatment. In this article, we propose the *SemAnatomy3D* framework, which demonstrates how the ontology-driven annotation of 3D-PSMs and of their anatomically relevant features (parts-of-relevance) can assist clinicians to document more effectively pathologies and their evolution. We exemplify the idea in the context of the diagnosis of rheumatoid arthritis of the wrist district, and show how feature extraction tools and semantic 3D annotation can provide a rich characterization of anatomical landmarks (e.g., articular facets, prominent features, ligament attachments) and pathological markers (e.g., erosions, bone loss). The core contributions are an ontology-driven part-based annotation method for the 3D-PSMs and a novel automatic localization and quantification of the OMERACT RAMRIS erosion score. Finally, our results have been compared against a medical ground-truth which was created by the rheumatologists.

Keywords Semantic annotation · patient-specific 3D model · computer aided diagnosis · rheumatoid arthritis · 3D indexing

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1 Introduction

Medical scans and 3D reconstructions contain a wealth of information about the patient's condition, which is often not explicit and computationally accessible. An important component that often accompanies medical images is the concept of region-of-interest (ROI) and its annotations, which aim at delivering an improved understanding of the data by means of critical commentaries. Ontology-driven annotations were introduced in medicine for coding the findings of clinicians (semantics) to images in a human and machine understandable way, opening the possibility to perform several other automatic operations on these processable knowledge. For example, the iPAD system [20] extends the functionalities of the image viewing platform OsiriX so that semantic tags from the RadLex ontology [12] can be linked to 2D medical scans. The application pushed forward by this extension is the support to an efficient retrieval of similar cases from clinical archives, which could improve greatly the automation of statistical studies in the field. However, the annotation process, that is the identification of ROI and the association of ontology's tags, is mostly manual and can only be applied to 2D DICOM images. A similar semantic annotation tool for medical images is RadSem, which leverages the MEDICO ontology to cover various aspects of clinical procedures [13]. RadSem uses an ontology-driven metadata extractor only for the image format DICOM, and allows the users to link images with anatomical annotations and clinical findings to generate an integrated view of a patient's medical history. The Medico system [22] applies an automatic detection and localization of anatomical structures within CT scans of the human torso and maps them to the concepts that are derived from FMA [19], ICD10 [16], RadLex. However, this approach is applicable only for CT data sets of human torso, and has been verified within a small set of sample images.

Advanced image segmentation and 3D reconstruction methods offer a whole spectrum of technologies to create detailed patient-specific 3D anatomical models (3D-PSMs), but a standard methodology to perform rich annotations of patient-specific 3D model is still lacking. Benefits of introducing part-based annotations for 3D-PSMs are many: tagging clinical explanation within an annotated 3D model can highlight the location of anomalies; interpretation becomes easier; identifying components becomes faster; and interactions become more effective when compared to an unannotated 3D model. Moreover, 3D part-based annotation offers a way to index relevant subparts in 3D reconstructed models, making them accessible more efficiently, and supports an integrated management of the 3D data together with its semantic content. The semantics-driven indexing of the 3D model and its relevant parts could also play a fundamental role in offering sophisticated information retrieval techniques to support speeding up the diagnosis process and improving accuracy in treatment of complex disease.

In this paper, we discuss the importance of a 3D part-based annotation system, using the context provided by Rheumatoid Arthritis (RA) as example of pathology affecting the hand district. To this aim, we first describe the characteristics of the annotation framework *SemAnatomy3D*, which has been presented recently in [4]. Semantics, as formalized in a biomedical ontology, is discussed for its role in the annotation process, as a conveyor of information supporting the documentation and diagnosis of rheumatoid arthritis. In particular, two modalities of annotation are described: a manual one, where the terminology is controlled by the ontology, and an automatic *top-down* method, which propagates the annotation of a 3D annotated template to the 3D-PSM. Also, the data model we have devised for coding part-based annotations is described, which is necessary to share 3D geometries enriched with semantics.

Novel contributions brought by this paper concern the development of a computational approach that integrates the semantic annotation with tools for measuring diagnostic metrics: erosion score and erosion map. Rheumatoid arthritis is a chronic inflammatory musculoskeletal disorder that affects the lining of joints, causing a painful swelling that can eventually result in bone erosion and joint deformity. In the clinical practice, the OMERACT score is a widely used quantitative parameter measuring the rheumatoid arthritis simpthoms. However, the erosion scoring is mostly a qualitative process that assesses bone erosion directly from the T1-weighted MRI images based on visual assessment. The OMERACT RAMRIS [17] reduces the inter-observer variability in erosion assessment task by introducing the EULAR-OMERACT RA MRI reference image atlas. Additionally, the manual evaluation of bone erosions volume from the MRI images is tedious, time consuming and not fully repeatable, especially for inexperienced users. In the diagnosis of rheumatoid arthritis, 3D-PSMs have not been yet considered, although they can provide interesting insights about the patient's condition and may help to minimize the manual efforts. Preliminary results about the computer-assisted evaluation of erosion scores was presented in [18], addressing the support to experts in the diagnosis of rheumatoid arthritis from MRI images.

The proposed method is based on an evolution of a 3D template model, used in the qualitative *top-down* annotation, which is further refined to provide a good estimate of the non-eroded 3D-PSM model. Similarity, or better, dissimilarity from the healthy anatomical areas is used to characterize erosion. A validation of the scoring results is also presented, which also demonstrate further the interest of the users with respect to this innovative methods to analyze 3D anatomical reconstructions. The complete annotation pipeline creates a bridge between the patient-specific geometry and the formal domain knowledge, and can be considered as a first step towards an intelligent 3D indexing for semantic-based retrieval from the medical knowledge-bases. The methods presented here are specialized to the context of rheumatoid arthritis of carpal bones, but in principle can support similar tasks in other clinical applications.

The paper is organized as follows: in Sect. 2, we discuss the requirements and design of the SemAnatomy3D framework, together with the developed knowledge formalization of the carpal area, and in Sect. 3 we describe the methods for descriptive quantitative annotation. Then, in Sect. 4 the computation of the erosion score within SemAnatomy3D is presented and Sect. 5 concludes the paper.

2 SemAnatomy3D: requirements and design

The requirements of a semantics-driven annotation framework have been studied within the scope of several international and national research projects (MultiScaleHuman [15], MEDIARE [1], POLITECMED consortium [2]). Lessons learnt from those projects gave us indications of the benefits of coupling computational approaches to biomedical data processing with knowledge management techniques, thus defining new features for the next-generation CAD systems.

The design, development, and validation of SemAnatomy3D were guided by a requirement analysis phase in which we first collected the basic requirements, opinions and perspectives through the distribution of questionnaires to clinical professionals and external research groups. We investigated the features that clinicians/radiologists expect from a patient-specific 3D model annotation system, and how they intend to employ them in their routine practice [5]. Experts mentioned that in the diagnosis of rheumatoid arthritis, it is crucial to have an idea about the patient's bone morphology, as well as position and characterization of the PoRs that can help quantifying diagnostic parameters in order to distinguish pathological cases from normal ones, or to determine the attachment areas of the ligaments. Besides comments related to the clinical relevance of the framework, we also received a positive feedback on the benefits of the part-based annotation of 3D-PSMs for facilitating interoperability, querying, reasoning and discovery in the 3D medical repositories.

This requirement analysis have led us to the following conclusions: a semantically rich and interoperable annotation system should - (i) express semantics not only of the whole 3D-PSM but also of the PoRs, where the PoRs can have either an anatomical significance (anatomical landmarks, prominent features) or pathological significance (erosion, lesion); (ii) describe the semantics of the data by relying on a formal knowledge of both anatomy and quantitative parameters/indicators; (iii) provide tools to compute automatically the quantitative parameters and diagnostic indicators from patient-specific 3D models. The envisaged system should also leave flexibility to adjust the annotations so that the user can tune the results obtained. SemAnatomy3D system consist of two main components - *SemAnantomy3D annotation tool* (Sect. 3) and *SemAnatomy3D knowledge-base*. The SemAnatomy3D annotation tool, and its graphical user interface, allows to annotate of a 3D-PSM and its parts-of-relevance. The SemAnatomy3D Knowledge Base, instead, stores the results of the annotation process adding relevant medical information to the 3D-PSM.

Formalization of knowledge about the carpal district The ontology we defined in our research investigations is focused on rheumatic arthritis and includes

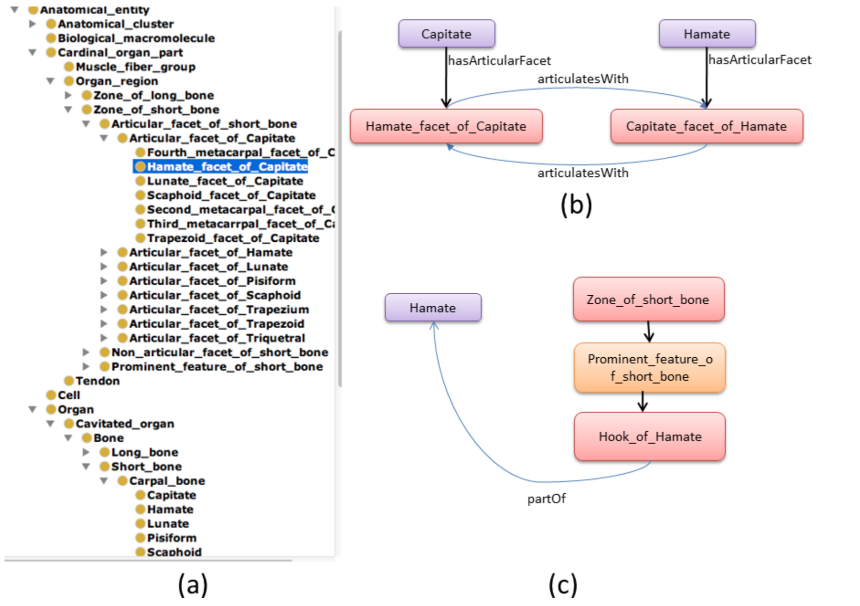

Fig. 1 Knowledge formalization: (a) taxonomy of carpal bones and PoRs; (b) articulation relations between the facets of Hamate and Capitate bones; (c) part-hood relation between Hook of Hamate and Hamate bone.

the medical background knowledge on carpal anatomy. The attributes formalized for each anatomical concepts reflect the parameters of interest for medical investigations. Also, the concept of patients and acquisition sessions/protocols were formalized. We represented this domain knowledge in OWL and we followed the knowledge re-use guidelines where possible [8]. To support the part-based annotation of 3D models of the carpal region, we consider the subpart of the FMA ontology related to this anatomical district. The extracted subpart is then enriched with the part-hood and articulation relations between the facets, as depicted on Fig. 1. This additional information was needed to support the user scenarios considered and was not included in the [1]Bioportal version of the FMA ontology. We kept the same labels for our two main OWL classes of the carpal region conceptualization (*Cavitated organ* and *Zone of Short bone* (Fig. 1) as in FMA for compatibility with other applications which use FMA ontology.

The formalization of medical background knowledge consisting of patient information, acquisition sessions, acquisition protocols, and relations between these concepts: patients undergoing acquisitions sessions, acquisition protocols performed during the acquisition sessions is captured by the MultiScaleHuman Ontology [14].

[1] http://bioportal.bioontology.org/ontologies/FMA

Table 1 Additional restrictions in SemAnatomy3D data model.

Restriction	Meaning
`oa:SpecificResource rdf:subClassOf sem3D:has source exactly 1 sem3D:Media`	`oa:SpecificResource` should have exactly one data file.
`Sem3D:3DModel rdf:subClassOf sem3D:has specific resource some oa:SpecificResource`	`sem3D:3DModel` can have some (one or multiple) specific resource(s).

Knowledge base and annotation data model The SemAnatomy3D knowledge base creates a bridge between the semantic representation and their geometry since the ontology-driven annotations are instances of the defined ontology. In the following, we describe the new data model and file format we have proposed for the storage of annotated 3D-PSMs.

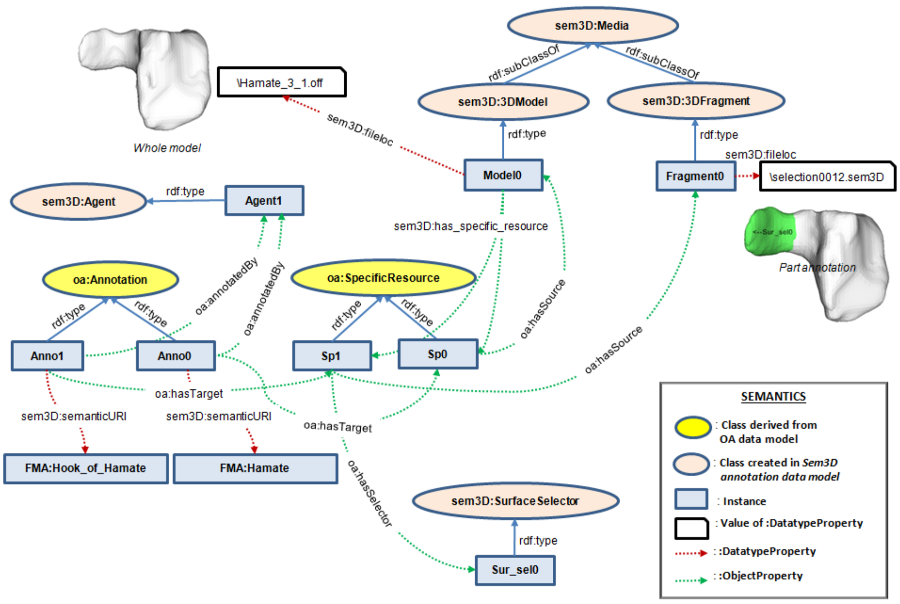

Fig. 2 SemAnatomy3D extension of OA model - saving of 3D surface fragment annotation.

The main role of the Sem3D annotation data model (Figs. 2, 3) is to manage the annotation so that it facilitates the interoperability, querying, reasoning, and discovery of 3D-PSMs. A number of semantic annotation data models have been proposed to support interoperability on the Web. These include the Annotea model [11], and the Open Annotation (OA) [10], but they do not provide sufficient specifications for annotating 3D-PSMs, their subparts, and varying-dimensional fragments. In particular, the OA data model [21] developed by W3C Open Annotation Community Group specifies a extensible data model to support interoperable annotations for enabling discovery and sharing of annotations without using a particular set of protocols.

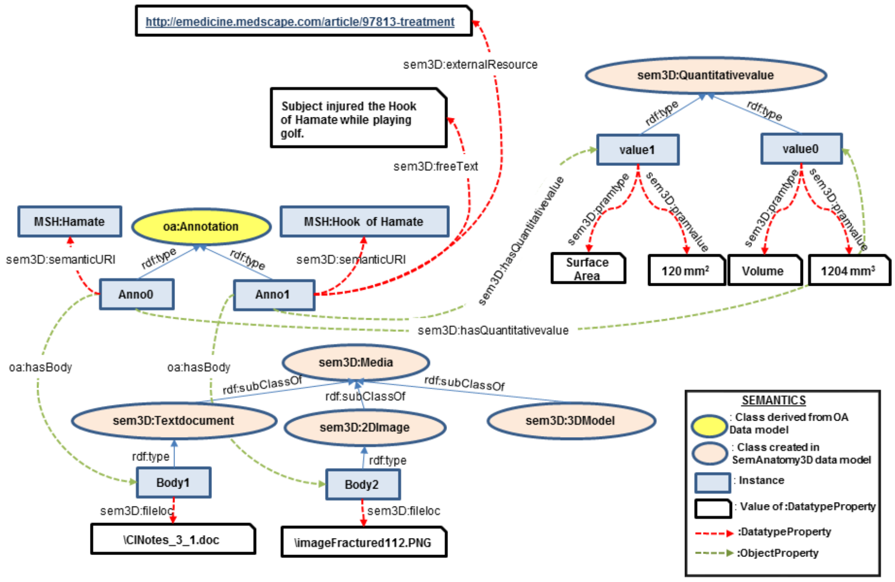

Fig. 3 SemAnatomy3D extension of OA model - formalization of annotation.

We extended the OA model to fulfill the main requirements of SemAnatomy3D annotation framework: i.e. to store the annotation of varying-dimensional 3D fragment and to support whole and part-based annotation with descriptive and quantitative attributes, multimodal annotation with textual tag/numeric value, 2D image or text file. In addition to the Open annotation model (OA) new concepts in the Sem3D annotation data model have been defined:

- `sem3D:3DFragmentSelector` is specified as a `rdfSubClassOf` the `oa:Selector` element to model different representations of the 3D PoRs (Sect. 2). It also has 3 subclasses to describe: points `sem3D:PointSelector`, edges - `sem3D:EdgeSelector`, and areal patches `sem3D:SurfaceSelector`.
- `sem3D:Media` stores various types of data format, e.g., 3D triangulated models, 3D fragments (.sem3D), 2D images, textDocument, which can either have their own annotation (*source of annotation*) or can be considered as annotation of another data (*body of annotation*).
- `sem3D:Quantitativevalue` stores a single numeric value parameter or scalar value map computed from the sem3D:Media. It can be considered as form of annotation. It has two rdf:DataProperties:`sem3D:paramtype` - describes the type of quantitative parameters, e.g., volume, area, curvature map; `sem3D:paramvalue` - stores the numeric value of the parameter.
- Restriction - In Table 1, we describe the restrictions that we implied on `oa:SpecificResource` and `sem3d:3DModel`.

In Fig. 2, the SemAnatomy3D annotation data model snapshot is related to the saving of a 3D surface fragment annotated as “Hook of hamate”, which represents the core classes and the relationships between. Each instance of `oa:Annotation` is linked to the instance of `oa:specific_resource` and each `oa:specific_resource` instance `oa:has_source` exactly 1 `sem:3D Media` instance. The `sem3D:Media` instance describes the data by storing the actual file location of annotation source. If a `oa:specific_resource` instance corresponds to a PoR (sub-part) annotation, then it will be linked with a specific `sem3D:FragmentSelector instance`, e.g., for "Hook of Hamate" it is linked with `sem3D:SurfaceSelector`. In Fig. 3, we show how the annotation instances are related to various information, such as semanticURI, external link, quantitative values in the SemAnatomy3D knowledge-base.

In addition, we have developed a simple and effective file format *.sem3D* with three main goals: support a faster way of reading, writing and rendering of 3D subpart annotation; be as simple as it can, so it can be customized for various applications; avoid storing redundant information. We came up with an index-based method of storing varying topological dimensional 3D fragments in a .sem3D file as follows: (i) *surface fragment in .sem3D* - we store only the index of the cells (triangle) belonging to the fragment, (ii) *Line fragment in .sem3D* - we store index of the points of belonging to the line fragment. We maintain adjacency of the points in the form of- $xy, yz, zk, \ldots$, (iii) *point fragment in .sem3D* - we only store the index of the points.

3 SemAnantomy3D: annotation tools

SemAnatomy3D supports both *descriptive* and *quantitative* annotation: the first describes patient-specific 3D carpal bone models and their parts-of-relevance by means of anatomical concepts/terms derived from the defined ontology (Fig. 4); the latter refers to the quantitative measurements and characterizations of the 3D-PSM via a set of geometric and shape analysis tools (Fig. 5). SemAnatomy3D allows the user to annotate the complete district (Fig. 4(a)), which is a relevant feature when performing an analysis of anatomical joints.

In our case-study of carpal bones, PoRs may corresponds to *surface patch (regions)* - articular and non-articular facets of the bone, prominent features such as scaphoid tubercle, hook of hamate, ligament insertion sites; *edges (polylines)* - boundaries between anatomical landmark regions, contours indicating abnormalities/disease affected regions, e.g. eroded regions; *vertices (points)* - extremal features of the bone, such the tip of a protruded facet, extreme pressure point. Thus, the realization of 3D annotation becomes more challenging in terms of PoR identification and management.

3.1 Descriptive annotation

Since the identification of the PoRs in a 3D-PSM is not trivial in terms of interaction, SemAnatomy3D supports both interactive and controlled selection of PoRs. The interactive way is manual, thus offering more flexibility to the user, while the controlled mode is automatic but may require some tuning.

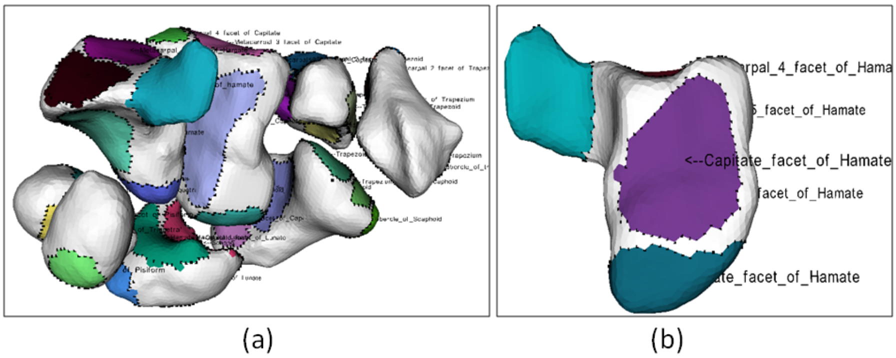

Fig. 4 SemAnatomy3D: (a)Annotation of a complete "Carpal region", (b)Individual annotation of Hamate bone.

Interactive annotation In order to allow the user to select the PoRs from a 3D model, an interactive tool palette has been incorporated within *SemAnatomy3D*, which offers multiple interaction tools, such as smart-cut, draw, paint and delete strokes, points' picking. For instance, in smart-cut the user can simply select a region over a 3D-PSM using a stretchable screen rectangle, and the system automatically computes the minimal cut in the 3D surface. In draw, the user can select only the visible portion of the 3D model using the same stretchable rectangle. Furthermore, the system allows for the modification of the boundaries by inserting/deleting elements from the selected PoRs. The main target of the tools is to make the 3D subpart selection an easy and quick task from the users' point of view. Afterwards, they can associate the corresponding conceptual tags to the selected PoRs by the interactive navigation of the reference ontologies.

Controlled annotation The automatic annotation method is based on the definition of a parametric 3D template model [6] that contains the anatomical landmark positions as parameters, registers the parametric template against the targeted model using an elastic transformation, and propagates the annotation onto the target model. Additional annotations, such as personal notes, text documents, can be added in a manual way after the automatic PoR recognition process.

To create the statistical model, we generate the mean shape of each carpal bone from the reconstructed healthy sample data by using an elastic shape analysis method guided by anatomical landmark-driven correspondences [6]. An important strength of the approach is that one to one correspondences between the training samples have been established while generating the mean shape. Given the mean shape μ and the registered sample population, for each class of carpal bone we obtain the most significant modes of variation by standard Principal Component Analysis (PCA) [3]. In Fig. 6, we present the principal modes of variation for Scaphoid bone (right hand). In the similar way, we conceive a set of statistical variances for each class of carpal bone.

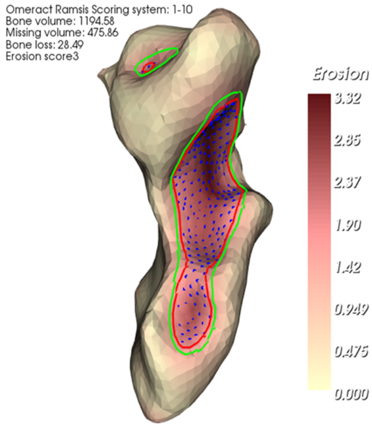

Fig. 5 Computation of the diagnosis metrics "Erosion score" and "Erosion map" from the 3D PSM.

After an elastic co-registration between the template model and the input model [4], the annotation is propagated from the vertices of annotated template to closest vertices of the target mesh. Then, the system automatically detects the boundary of each annotated surface fragments, and a filter based on the 1-ring neighbors adjacency generates an annotated region with smooth boundary which can be further refined by the user interaction tools described in Sect. 3. Fig. 4 presents an example of the automatic annotation and Fig. 7 shows the annotation of an eroded hamate bone, affected by a rheumatic arthritis at stage 2, where the PoRs are correctly recognized also in highly eroded regions.

The global complexity of the registration algorithm is $O(N_x \log N_y)$ where N_x and N_y represent the number of vertices in the template and the target model. The propagation of annotation is done in the liner time $O(N_p)$, where N_p is the number of vertices belong to a landmark. In a standard machine, our method takes a few seconds to annotate 6-8 anatomical landmarks in a 3D model, where the total number of vertices 3080 and number of triangles 5156.

3.2 Quantitative annotation

In clinical investigation, it is important to capture the quantitative aspects of the patients' data and to derive a detailed characterization of anatomy that illustrates various facets of medical knowledge, e.g. anatomical, functional, and pathological ones.

In the case study of rheumatoid arthritis, we developed a 3D shape analysis library to automatically compute some of the quantitative parameters directly from a 3D-PSM or from its annotated PoRs. Additionally, we incorporated a specialized set of feature descriptors to characterize automatically the carpal district, in terms of functional regions, e.g., articulation and adjacency. A few

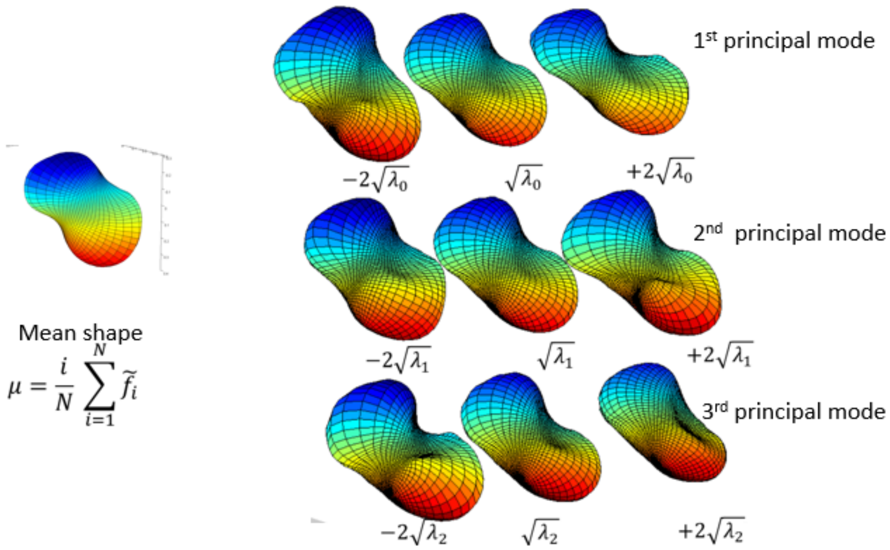

Fig. 6 Principal modes of variation: Scaphoid bone.

Table 2 List of parameters to support the characterization of rheumatoid arthritis.

Computation	Input	Output	Parameters
Quantitative measurements	3D-PSM	Scalar value	Bone Volume (BV)
			Bone Surface (BS)
			Bone Length (BL)
			Bone Volume/ConvexHull Volume (BV/CV)
		Scalar value map	Curvature map (Mean, Gaussian) (CMap)
			Average geodesic (GMap)
			Distance from CovexHull (HMap)
	Complete district (a set of 3D-PSMs)		Shadow Map (SMap)
			Inter-bone adjacency graph
		Scalar value	Carpal height and width
	3D-PSM and annotated PoRs	Scalar value	Area of articulation region
			Geodesic distance between landmarks
Dissimilarity measurement from normality	Statistical template model and target 3D-PSM	Scalar value map	Erosion map
		Scalar value	OMERACT RAMRIS erosion score
		Identified PoR	Eroded region

parameters do not have an immediate clinical significance but they are still useful to evaluate the potential of a rich 3D-PSM characterization in clinical investigation. In Table 2, we summarize the parameters we computed to characterize rheumatoid arthritis. The quantitative measurements have been developed using state-of-the-art algorithms for shape analysis, as detailed in [7]. In Sect. 4, we introduce a novel approach to estimate the erosion score through the dissimilarity measurements from normality.

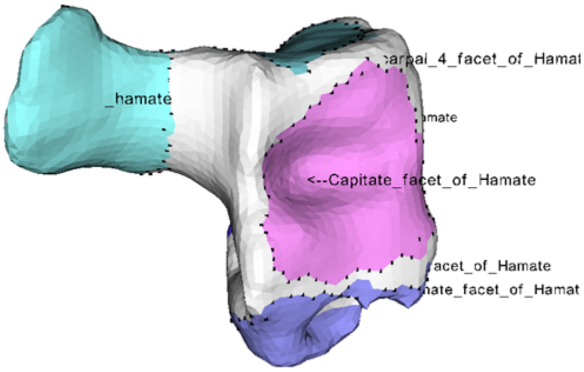

Fig. 7 Annotation of a patient-specific Hamate - eroded.

4 Computing erosion score with SemAnatomy3D

In the following, we discuss the detection of anomalies (e.g., bone loss) and the computation of pathological markers (e.g., OMERACT RAMRIS erosion score [17]). More precisely, we tackle the computation of the erosion score by measuring the dissimilarity from the "normal" shapes. Defining *shape normality* in anatomy is not trivial, since the variability of shapes even within the healthy samples is considerable. Recently, statistical shape modeling has been proven a successful method for capturing anatomical variabilities. However, the performance of statistical shape modeling crucially depends on the way anatomical regions of inter-patient shapes are mapped to each other, and such correspondence is in general difficult to fulfill for 3D anatomical shapes.

In our novel method, we integrated the template introduced in Sect. 3 with a semantics-based structural descriptor to capture shape variance. After devising the principal shape variations for each class, we implement an automatic method that identifies the most similar shape variation, where the relevant anatomical features (landmarks) are "similar" to the target model. We compute a semantics-based structural descriptor of the target shape as well as of each shape variance, depending either on annotated articulation regions or on annotated prominent bony features. Fig. 8 shows the *semantics-based structural descriptor* for a patient-specific scaphoid bone where the black node is the center of mass of the 3D model, the other colored nodes represent the corresponding annotated regions, and the edge weight is computed as the Euclidean distance from the center of mass and the connected node. We describe the descriptor as an undirected weighted graph where the nodes are labeled with semantic tags of the corresponding annotations. The edge attribute represents the Euclidean distance from the center of mass, which highlights the distribution of the object with respect to its barycenter.

We saved the pre-computed values of the descriptor for the variances of each bone class, while for the target shape we compute the descriptor on the

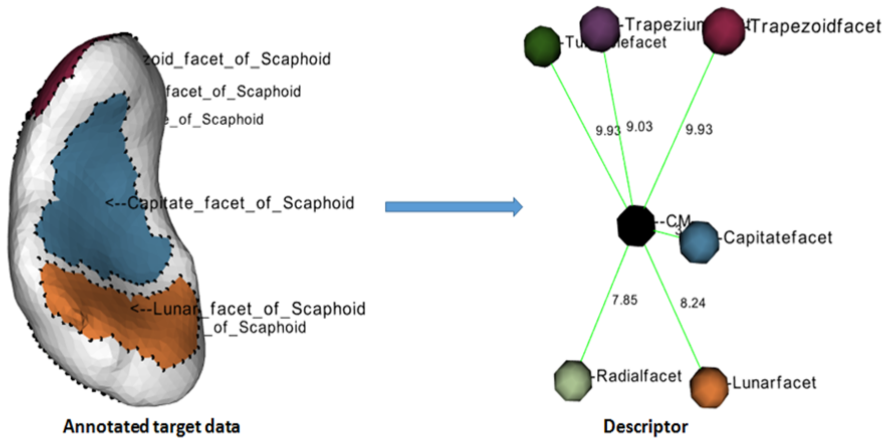

Fig. 8 Semantics-based structural descriptor for scaphoid.

fly by using the template-based automatic annotation method. To retrieve the matching variance, we normalize the edge weights for the target descriptors with respect to the maximum edge weight, since the variances being generated from the parameterized sample sets are already normalized. Afterwards, we execute an iterative search mechanism to retrieve the "best match" covariance where the correspondence between the nodes of the target shape descriptor and the ones of the covariances descriptors are already established by the semantic tags. Thus, a "best matching" candidate is simply picked, where the difference in total edge weight is minimum between the target and variance descriptors.

Thanks to the statistical template, we adopt a double characterization using two distinct metrics: "Erosion score" and "Erosion map". The two types of metrics have complementary strengths in depicting local and global morphology of the bone. To measure the erosion score, we follow the standard OMERACT scoring system [9], which grades the bone loss due to erosion on a 0-10 scale based on percentage of estimated bone volume loss. Then, the co-registration aligns the centroid of the statistical template with the target shape and applies an uniform scaling (Fig. 9 (a)) and iterative rotations based on the principal axes alignment which optimizes the distance computed as the square root of the average of the sum of squares of the closest point distances (Fig. 9 (b)).

After the optimal alignment, we measure the percentage of bone loss as $Boneloss = \frac{BV_R - BV_T}{BV_T} \times 100$, where BV_R refers the volume of co-registered model, BV_T is the target bone volume. The score is derived as: $0 \leq Boneloss \leq 1$ erosion score is 0, $1 < Boneloss \leq 10$ erosion score is 1, $10 < Boneloss \leq 20$ erosion score is 2, and so on. The erosion score offers a global characterization of pathological data, also it does not bring any knowledge about the exact

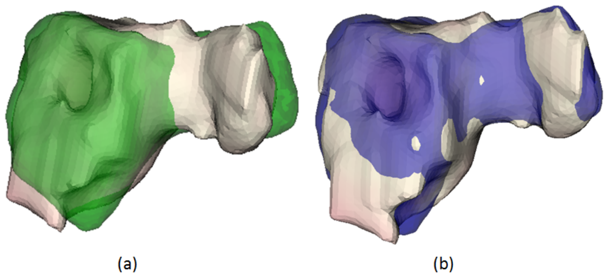

Fig. 9 Rigid registration steps (Case-study: 3D-PSM of Hamate bone): (a) coarse registration based on translation and uniform scaling (registered template in green); (b) refinement based on iterative rotation (registered template in blue).

locations of erosion. We propose a novel metric "Erosion map" in order to detect the exact location of the erosion through the rigid co-registration of a healthy statistical template. The Erosion map is evaluated upon the targeted data by measuring the vertex-wise Euclidean distance from the co-registered template model. In the erosion map, the scalar value of a vertex p of the target model is define as $ErosionMap(p) = \min(d(p, q_1), d(p, q_2) \ldots, d(p, q_n))$, where q_i is the ith vertex of the co-registered template and n is the total number of vertex in the template model. After the erosion map computation, contours have been drawn based on a pre-define range of values (Fig. 5). This investigation can recognize specific area of anomalies for fine grain analysis.

In a standard machine, our method takes a 2 - 3 seconds to compute the erosion in a regular 3D bone model, where the total number of vertices 5156 (see Fig. 10), and 7 - 8 seconds to compute the erosion in a high resolution mesh (vertices > 20,000).

Validation A validation with expert evaluation has been performed on the various levels of our quantitative measures: eroded volume, erosion location, and the OMERACT RAMRIS erosion scoring. As a ground truth, we have utilized an online clinical database [23] which consists of MRI images and corresponding manually segmented surface models along with the expert-evaluated erosion score value. The ground truth was created by a group of rheumatologists from the *department of clinical rheumatologist (DIMI), University of Genova (Unige)*, and they were assisted by a professional computer aided diagnosis system [18]. In this study, 30 patients affected by rheumatic arthritis (RA) and 10 healthy patients have been considered, and a total $40 \times 8 = 320$ 3D carpal bone models have been evaluated. Results on eroded volume and OMERACT scoring comparison is presented in Table 3, where the "Manual:% of bone loss" column represents expert-assessed value of the bone loss, and the "SemAnatomy3D: % of bone loss" column shows the automatically measured value where the bone loss and erosion scoring have been computed according to method described.

Table 3 Comparison for Lunate bone.

Patient id	Manual: % of bone loss	Manual: scoring	SemAnatomy3D: % of bone loss	SemAnatomy3D: scoring
1543	0	0	0	0
5778	0	0	0	0
1432	1.17	1	0.95	1
3425	4.37	1	3.97	1
6264	0	0	0	0
5509	0	0	0	0
1984	0	0	0.67	1
2996	0	0	0	0
2736	0	0	0	0
1646	0	0	0.61	1
3218	1.14	1	0.74	1
2513	0	0	0.63	1
3107	0	0	0	0
1964	24.56	3	23.78	3
2625	0	0	0	0
3321	0.43	1	0.36	1
2095	0	0	0	0
1815	11.89	2	10.79	2
4817	16.69	2	15.73	2

In most cases the automatic evaluation scoring correlates with the ground truth (green text), however the eroded volume measured by the automatic algorithm differs a bit compared to the manual assessment mainly because the manual evaluation has been performed on the voxel space, whereas the automatic evaluation has been performed on 3D shapes. In a few cases (red text) a mismatch in the scoring observed, mainly for healthy data. After discussing the mismatch with clinical experts, we derived that it is mainly caused either by a specific healthy shape variation, which is not captured by the statistical template, or due to a segmentation error which was manually corrected during the expert's assessment.

Additionally, the manually evaluated eroded surfaces were compared with the erosion location identified automatically by the "Erosion map" metric (Fig. 5). Fig. 10 represents the comparison result, where the manually evaluated eroded surface has been colored according to distance from the automatically evaluated erosion location. In this case, the automatically evaluated result closely matches with the ground truth.

Furthermore, for other non-erosive pathological data sets where the bone shape differs from the normality (e.g., osteoarthritis, avascular necrosis) the erosion map may highlight also the area of these anomalies and behaves more like an "Abnormality map".

5 Conclusions and perspectives

In this study, we have proposed an extension of the *SemAnatomy3D* to compute expressive characterizations of 3D-PSMs, in the context of computer-

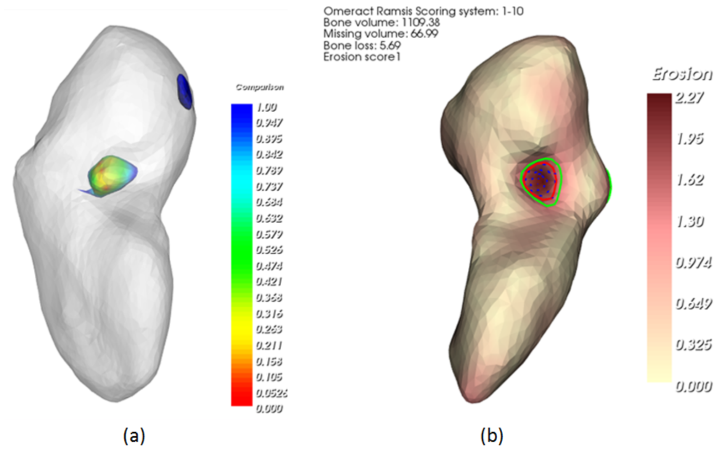

Fig. 10 Erosion location comparison result: (a) manually eroded surface colored according to the distance from automatic evaluation; (b) automatic evaluation result.

assisted diagnosis of rheumatoid arthritis. The novel methods introduced for extracting the erosion map and evaluating quantitatively the erosion score have been presented and discussed with respect to the score assigned by experts in the domain, demonstrating the usefulness of the approach proposed. We believe that these examples are useful to demonstrate concretely the potential of 3D part-based annotations to open new perspectives for computer-assisted diagnosis systems, until now dominated by image content rather then 3D models.

SemAnatomy3D integrates computer-processable knowledge and geometry processing tools which, together, contribute to support both automatic and manual part-based annotations of 3D anatomical models. The results of this advanced semantic enrichment are stored using a novel 3D annotation data model, which enables sharing of the medical reasoning within and across communities of specialists. The fine-grained shape characterization of anatomical structures, properly annotated, can support efficient semantic-based retrieval from medical knowledge-bases, enabling the analysis of the 3D-PSM with information related to anatomy and pathology, and consequently efficient clinical reporting of patient's status. Information retrieval and content-based retrieval mechanisms could be established on this enriched vision of medical knowledge-bases, contributing to the establishment of novel investigation procedures in the medical field. For instance, let us consider the following scenario: A clinician, when consulting a surface fragment of a 3D-PSM annotated as an articulation facet, might be willing to consult adjacent facets of the fragment with which it articulates. In fact, in the case of RA, if one articulation facet in a joint contains erosion or lesion, there can be a certain chance of erosion in adjacent articulation regions. A query addressing this search could be expressed as *"Where could be located a probable chance of erosion in "Carpal region" of patient XX, if "Capitate facet of Hamate" has average erosion value 2.5?".*

SemAnatomy3D could answer this query, since the anatomical formalization (Sect. 2) captures adjacency relations between the articular facets of bones, together with annotated quantitative parameters. Among the quantitative parameters, there is the average erosion value therefore we could first retrieve the adjacent facets, and then filter the results so that only those whose average erosion value falls inside the required range.

We envisage that content-based retrieval could be integrated easily in the framework, supporting reasoning based on shape similarity: shape is indeed essential when analyzing anatomy and difference to canonical forms is a common indicator of pathological conditions. For instance, we could imagine that a clinician wants to look for other patients having some analogies to the case in question, as expressed by a simple query such as n: *Retrieve the cases where "Capitate facets of Hamate" are similar to that of the Patient X's one?.* One way to establish the similarity between cases is querying the knowledge-base for 3D models of patients annotated with similar quantitative parameters to those of the given patient. Another way to approach the problem would be to make a query by example to the knowledge-base using the patient's 3D model of hamate as query model.

Similarity-based reasoning could be very useful also to analyze the evolution of a pathology, in a typical follow-up process. An advanced query related to this example scenario could be summarized as *"Retrieve all "Articular facet" (s) of patient XX "Carpal bone" where erosion increased compared to the last acquisition session".* *SemAnatomy3D* supports the annotation of the 3D models of the same PoR (e.g., capitate facet of hamate), belonging to the same patient associated with two different acquisition sessions and ultimately store their annotations. Based on this, to support follow-up monitoring of the patient, the query could first look for the 3D-PSMs created from different acquisition sessions of the same patient XX, which he/she underwent at different times. Then, filter the answer set to get 'Articular facet" PoR annotations of carpal bone with their quantitative measurements. Finally, pairs of annotations of the same PoR, distinguished by their acquisition time, could be compared and only those annotations which exhibit a difference returned.

The adoption of 3D annotation systems tailored to the clinical domain, as we proposed with SemAnatomy3D, allow us to envision distributed medical repositories where querying, reasoning and discovery of 3D-PSMs can be done over the Web.

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