A General Approach to Shape Characterization for Biomedical Problems

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Abstract. In this paper, we present a general approach to shape characterization and deformation analysis of 2D/3D deformable visual objects. In particular, we define a reference dynamic model, encoding morphological and functional properties of an objects class, capable to analyze different scenarios in heart left ventricle analysis.
The proposed approach is suitable for generalization to the analysis of periodically deforming anatomical structures, where it could provide useful support in medical diagnosis. Preliminary results in heart left ventricle analysis are discussed.

1 Introduction

Deformable structures arise frequently in human anatomy and, in many cases, their deformation modes are of key importance in understanding the functional properties of the related organs and assessing their health-state. The main example is given by cardiac dynamic analysis, since many heart pathologies are correlated to the deformation pattern of the organ. In cardiac analysis, well-established imaging techniques are of great support in medical diagnosis, since they allow to acquire video sequences of the heart, from which its dynamical behavior can be inferred. However, the interpretation of the acquired data (temporal sequences of 2D/3D images, possibly from different imaging modalities) is difficult or, at least, time consuming; in daily practice, sometimes, physicians extract the most salient frames from the video sequence (end diastole and systole) and perform direct comparison among images in the selected subset. It is likely that, considering the full video sequence, more precise and rich information about the state of the heart can be discovered.

Motivated by these problems and extending the works [1, 2], we believe that it is fruitful to define, in some generality, the concept of periodically deforming visual objects (see section 2 for a precise definition) and to propose a methodological approach to their study.

Besides providing modules for structures reconstruction and characterization, that have their own importance in biomedical applications as automatic tools to speed up diagnosis, the main idea is to define a reference dynamic model of an

objects class: this model can be understood as an encoding of morphological and functional properties of a periodically deforming object during its full deformation cycle. In particular, shape changes and evolution of local object properties are depicted in a coincise form in the reference dynamic model, thus allowing for deformation analysis and deformation pattern classification.

The paper is organized as follows. In section 2 we define the class of objects we are interested in, making explicit the necessary assumptions. Then in section 3, the proposed approach is outlined and its basic modules leading to the reference dynamic model are described in detail. More precisely three modules are considered: *object reconstruction* (sec. 3.1), in which every object is reconstructed in Euclidean space as a collection of manifolds, *object characterization* (sec. 3.2), in which local shape descriptors and functional features are coded into property functions and, finally, *deformation pattern assessment* (sec. 3.3) where the reference dynamic model is actually built. Preliminary results in heart dynamic analysis are then presented in section 4, whereas conclusions and directions for further work are briefly discussed in section 5.

2 Periodically deforming visual object

A visual object O embedded in the background space $\Omega \subset \mathbb{R}^d$ $(d = 2, 3)$ is a collection

$$O = \{(V^\alpha, P^\alpha)\}_{\alpha=1,2,\ldots,k}$$

where each V^α is a smooth manifold (possibly with boundary) embedded in Ω and $P^\alpha : V^\alpha \to \mathbb{R}^{d(\alpha)}$ is a smooth *properties function* assuming its values in a suitable properties space.
The smoothness assumption is a quite common hypothesis in computational anatomy (see e.g. [3]) and it is satisfied in practice to a large extent; it implies for example that differential geometric properties (like normals, curvatures,...) can be computed everywhere. We use, moreover, collection of manifolds -instead of a single one- to be able to describe object subparts (possibly of different dimensionality) by attaching them specific salient attributes via a dedicated properties function. For example, in heart left ventricle modelling, the object of interest is the myocardium, that can be modelled as a 3D manifold, whose boundaries are two surfaces: the epicardium and the endocardium. It is convenient to attach to the boundary surfaces a different (actually richer) set of attributes than those used for internal points.

A deforming visual object $\mathcal{O} = (O_t)_{t=1,2,\ldots}$ is a temporal sequence of visual objects satisfying some smoothness constraint. Each $O_t = \{(V^\alpha, P^\alpha)\}_{1\leq\alpha\leq k}$ should be regarded as the *snapshot* of the deforming object at time t.
We require that each manifold V_t^α appearing in the snapshot at time t can be smoothly deformed into V_{t+1}^α in the subsequent snapshot. Tears or crack of any object subpart are, therefore, ruled out; moreover, in such a way, we avoid dealing with changes in topology, that would require to model shape transitions, a task far beyond our present scopes.

Finally, a periodically deforming visual object is a deforming object for which there exists an integer T such that $\forall t: \ O_t = O_{t+T}$. In other words, the deforming object depicts a periodic motion; thus, a periodically deforming object is characterized by a finite list of snapshots $(O_1, O_2, \ldots, O_T)$, which will be referred to as its deformation cycle.

We make a final assumption about the data available to describe a periodically deforming visual object. It is assumed that a sufficiently rich set of synchronous signals and images, possibly from different modalities, has been acquired so as to represent faithfully a physical body or phenomenon of interest. In particular, the data set should include at least one 2D/3D image sequence $(I_t)_{1 \leq t \leq T}$, from which morphology and regional properties of the object can be inferred.

3 Methodology definition

With the previous assumptions, a reference dynamic model of an object of interest is constructed by coding the dynamics of the object in a rich representation of its shape and functional properties.
The approach consists in three modules, each one performing specific tasks. Essentially, the first two modules are dedicated to extract a suitable periodically deforming visual object from image data. Then the periodically deforming visual object is analyzed and used to construct the reference dynamic model. A more precise outline of the modules used to obtain the aforementioned model is as follows:

Object reconstruction: For each phase t, the collection of manifolds $\{V_t^\alpha\}$ is identified and reconstructed in 2D/3D space by applying neural algorithms to the image sequence $(I_t)_{1 \leq t \leq T}$;

Object characterization: Morphological features and dynamic descriptors are extracted and coded in a property function P_t^α that for each point x of the manifold V_t^α returns the property vector $(P_1^\alpha(x), \ldots, P_m^\alpha(x))$, where each P_i^α represents one of the selected features;

Deformation pattern assessment: Suitable and significant shape descriptors are extracted and spatial distribution of the property functions are evaluated in order to obtain a description of the object dynamics.

In the following sections, these steps are described in more details.

3.1 Object reconstruction

The 3D reconstruction of the visual object $\mathcal{O}$ is achieved via voxelwise classification, that is by labeling each voxel in the image domain with semantic classes which describe voxel membership to the collection of manifolds $\{V_t^\alpha\}$.

The classification is performed applying an advanced neural architecture to a set of extracted features. The involved features can be divided into two classes.

First, low-level features are considered: they are context-independent and do not require any knowledge and/or pre-processing. Some examples are voxel position, gray level value, gradients and other differentials, texture, and so forth. Middle-level features are also selected, since voxel classification can benefit from more accurate clues, specific of the problem at hand. In particular, if an intrinsic reference system can be individuated to describe the object shape, it can be used to define a relative voxel position. If, in addition, a priori information about the object shape is available, a reliable clue for detecting edges in the images is given by the gradient along the normal direction to the expected edge orientation.

Moreover, a multiscale approach is adopted: the features are computed on blurred images, supplying information about the behavior of the voxel neighborhood, which results in a more robust classification.

The set of selected features are processed to accomplish the voxel classification by means of a Multilevel Artificial Neural Network (MANN), which assures various computational advantages [4]. For each voxel x, its computed features vector is splitted into vectors $\mathcal{F}_k(x)$, each one containing features of the same typology and/or correlated. Then each $\mathcal{F}_k(x)$ is processed by a dedicated classifier based on an unsupervised Self Organizing Maps (SOM) architecture. The set of parallel SOM modules constitutes the first level of the MANN which aims at clustering each portion of the feature vector into crisp classes, thus reducing the computational complexity. The output of this first level is then passed to a second and final level, consisting in a single Error Back-Propagation (EBP) module, which supplies voxel classification.
Its output describes voxel membership to the various manifolds V_t^α in the collection $\{V_t^\alpha\}_{1\leq\alpha\leq k}$.

3.2 Object characterization

The reconstructed object is further characterized by assigning a significant properties function $P_t^\alpha : V_t^\alpha \rightarrow \mathbb{R}^{d(\alpha)}$ to each manifold V_t^α.

Three types of properties are considered:

- intensity based properties;
- local shape descriptors;
- local dynamic behavior descriptors.

Examples of properties of the first type are gray level value, gradients, textures and so on. They are extracted form the image sequence I_t –the one which leads us to object reconstruction. If data collected from other imaging modalities are available, after performing registration, we can fuse this information to further annotate the object (for example, in the case of the heart, information regarding perfusion and metabolism, obtained e.g. by means of PET imaging, can be referred to the reconstructed myocardium). Geometric based properties, belonging to the second type, are extracted directly from the collection of manifolds $\{V_t^\alpha\}$, and are essential to describe locally the shape of the object. Again,

we may distinguish between context independent features (automatically computable for every manifold of a given dimensionality, such as Gaussian and mean curvature for surfaces) and problem-specific properties.

Finally, the local dynamic behavior may be described by properties borrowed from continuous mechanics (such as velocity field and strain tensor); they, however, require, at least, local motion estimation, that we haven't pursued yet.

3.3 Deformation pattern assessment

The periodically deforming visual object obtained in the previous steps can be used to assess the dynamic behavior of the object and identify its deformation pattern. However, the voxelwise characterization of the reconstructed objects is not suited for state assessment. Indeed, the given description of the whole objects (collection of manifolds described by functions) has a dimensionality far too high to make the problem computationally feasible. Moreover, it would be essential to be able to compare anatomical structures belonging to different patients and, at the moment, the idea is to use a deformable model (given for example by mass-spring models [5]) and to normalize every instance of anatomical structure to that model: in this way anatomical structures (belonging to the same family) are uniformly described and can be then compared.

Combining these two issues, we should look for a new set of 'more intrinsic' features $\mathcal{F}_t$ that should be enough simple and, at the same time, capturing essential information about the objects.

To obtain these new kinds of features, global information about the objects can be extracted from the properties function, without introducing any model. For example, one may consider the 'property spectrum', by which we mean the probability density functions (PDF) of a given component of the property function $P_t^\alpha(\cdot)$. This consists in a function capturing how the property is globally distributed; thus, comparison of different property spectra is directly feasible; to reduce dimensionality, moreover, it is effective to compute the momenta of the PDF (mean, variance,...).

However, properties spectrum does not convey any information at all about regional distribution of the property. In practical situation, this is a drawback which cannot be ignored: for example, a small 'highly abnormal' region may not affect appreciably the PDF, but its clinical relevance is, usually, not negligible. Hence, spatial distribution of properties has to be analyzed; in some cases, approaches which do not need a refined model of the object (e.g., Gaussian image, spherical harmonics or Gabor spherical wavelets) may be suitable. However, in general one should define a model of the objects (whose primitives -elementary bricks- are regions, patches or landmarks) and then propagate it to the set of instances to be analyzed by using matching techniques. Then, we may consider the average of a property on regions or patches (or the value in a landmark) as a good feature, since comparisons between averages on homologous regions can be immediately performed.

Following this recipe, a vector of features $\mathcal{F}_t$ with the desired properties is obtained for each phase of the cycle. The deforming object is then described by

the dynamics of the temporal sequence of feature vectors obtained at different phases of the deformation cycle.

A further fruitful feature transformation may be performed exploiting our assumptions on deformable visual objects. Indeed, the smoothness of deformations implies that a visual object has mainly low frequency excited deformation modes. We extend this slightly assuming that this holds true also for the features lists $(\mathcal{F}_t)_{1 \leq t \leq T}$. We assume that the fundamental frequency of the motion is also the main component of each feature tracked on time. With these assumptions, an obvious choice is given by the Fourier transform, followed by a low pass filter, which supplies a new features vector Θ.

The evaluation of the above mentioned parameters $\mathcal{F}_t$, at each phase t, implicitly codifies information regarding object dynamics. Actually, we avoid defining a complex model of the object kinematics and exploit its periodic characteristic by constructing a rich representation of each phase of the deformation cycle.

4 Results

An elective case study for the presented methodology is cardiac analysis, whose clinical relevance can be hardly overestimated. We restrict our analysis to the left ventricle (LV) that, pumping oxygenated blood around the body, is the part of the heart for which contraction abnormalities are more clinically significant.

The proposed methodology is, of course, not universal, in the sense that there are some intrinsic limitations that prevent it to be potentially applied in any scenario. Indeed, our analysis is limited to a single deformation cycle and so only pathologies that affect every deformation cycle can be considered. Moreover, we require that physiological and (selected) pathological states induce different feature dynamics. This requirement is not too restrictive; actually, it is well known that many pathologies are correlated to abnormal shape patterns at end systole.

The LV structure is modelled as a 3D manifold (the myocardium) with boundary. The boundary has two connected components which are the surfaces corresponding to epicardium and endocardium.

We describe henceforth how the steps of the methodology are applied. First, the deformable visual object structure is extracted from the available data, consisting in a sequence of short axis gradient echo MR images, acquired with the FIESTA, GENESIS SIGNA MRI device (GE medical system), 1.5 Tesla, TR = 4.9 ms, TE = 2.1 ms, flip angle 45° and resolution $(1.48 \times 1.48 \times 8)$ mm. Sets of $n = 30$ 3D scans, consisting of $k = 11$ 2D slices, were acquired at the rate of 30 ms for cardiac cycles [diastole-systole-diastole]. Various clinical cases were considered, for a total of 360 scans, corresponding to 12 cardiac cycles.

To perform reconstruction, we first used a pre-processing step devoted to the automatic localization of the left ventricle cavity (LVC) [6].

The located LVC is then exploited to define an Intrinsic Reference System (IRS), given by a hybrid spherical/cylindrical coordinates system. This choice is dictated by the fact that LV approximately resembles a bullet-shaped structure;

moreover, in the IRS, image partial derivatives w.r.t. radial coordinate are an efficient clue for heart surfaces detection.

The IRS is used to extract the following features for voxel classification:

- Position w.r.t. IRS
- Intensity and Mean intensity (computed applying Gaussian filters)
- Gradient norm $||\nabla I_t||$
- Partial derivative in the radial direction $\frac{\partial I_t}{\partial r}$.

Using the 2-level ANN, voxels are classified on the basis of their features vector as belonging or not to epi- and endocardial surfaces. More in detail, the set of extracted features is divided into two vectors $\mathcal{F}_1$, $\mathcal{F}_2$ containing respectively position, intensity and mean intensity, and position, gradient norm and partial derivative $\frac{\partial I_t}{\partial r}$. The position w.r.t. IRS is replicated in both vectors because it reveals salient for clustering both features subsets. Then, the first level of the MANN consists of two SOM modules, which have been defined as 2D lattice of neurons and dimensioned experimentally, controlling the asymptotic behaviour of the number of excited neurons versus the non-excited ones, when increasing the number of total neurons [7].

A 8×8 lattice SOM was then trained, according to Kohonen's training algorithm[8], for clustering the features vector $\mathcal{F}_1$, while $\mathcal{F}_2$ was processed by a 10×10 lattice SOM.

A single EBP module has been trained to combine the results of the first level and supply the final response of the MANN. The output layer of this final module consists in two nodes, which are used separately for reconstructing the epicardium and the endocardium. Since each cardiac surface divides the space into two connected regions (one of which is bounded), each output node can be trained using the signed distance function with respect to the relative cardiac surface. In this way, points inside the surface are given negative values, whereas positive values are given to points in the outside. Henceforth the surface of interest correspond to the zero-level set of the output function.

Different architectures have been tested, finding the best performance for a network with only one hidden layer of 15 units, trained according to the Resilient Back-Propagation algorithm [9].

The voxel classification, supplied by the MANN, may be directly used for visualization purposes by using an isosurface extraction method, as shown in figure 1.

Characterization of the reconstructed structure is obtained annotating every voxel with intensity, Gaussian and mean curvature, wall thickness and IRS properties. In particular, Gaussian and mean curvature have been included as shape descriptors whereas wall thickness, which is a classical cardiac parameter, is one example of problem-specific property: it is defined as the thickness of the myocardium along a coordinate ray and it is expected to increase during contraction (since myocardium, being almost water, is, with good approximation, incompressible).

Fig. 1. Different views of the rendered left ventricle at end diastole. The surfaces are obtained applying marching cubes on the two output functions of the network. To eliminate satellites, a standard island removing procedure is applied.

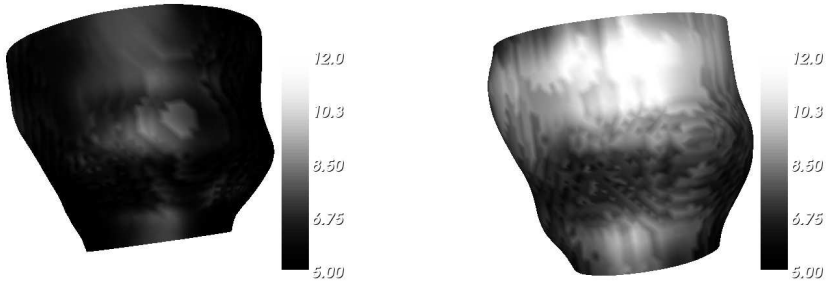

Fig. 2. Wall thickness at end diastole and systole, shown as an attribute of epicardial surface. Estimation is performed according to the centerline method and values are expressed in millimeters.

This characterization is translated in a more amenable form by computing properties spectrum and regional features. In computing spectrum, coordinates w.r.t. IRS have been disregarded, with the exception of radial coordinate; intensity has also been excluded. For any property only mean and variance have been considered. For computing regional features, so far, we used a popular model of the LV (see [10] for a review of 3D-cardiac modelling). In 2D, as shown in Figure 3, it is defined by the intersections of cardiac surfaces with a pencil of equally spaced rays. The 3D version is obtained by stacking the 2D construction along the axis of the LV.

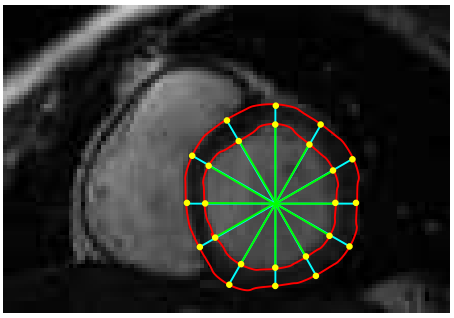

Fig. 3. The pencil of equally spaced rays used to computed local features.

5 Conclusions and further work

In this paper, we define a reference dynamic model, encoding morphological and functional properties of an objects class, capable to analyze different scenarios in heart left ventricle analysis. In particular, a framework for the shape characterization and deformation analysis has been introduced for the study of periodically deforming objects.

This framework consists of several modules performing a) object reconstruction, b) object characterization, c) pattern deformation assessment. Solutions to specific tasks proposed in each module are, to a large extent, independent and may be combined with other methods, thus broadening the potential application field of the framework. In particular, an approach based on multi-level artificial neural network has been selected as a general purposes strategy for object reconstruction, motivated by the promising results presented in [4]. A quantitative evaluation of segmentation performance, based on comparison between images automatically segmented and images annotated by a committee of expert observers, however, is still in progress.

The elective case studies are represented by the analysis of heart deformable anatomical structures. Actually, for demonstrating the effectiveness of the proposed framework, we have shown the preliminary results in the study of the heart

left ventricle dynamics. The next step will be to employ the obtained results for defining a general method to classify the state of the deformable object, and, in particular, the physio-pathological states of the left ventricle.

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