A Methodological Approach to the Study of Periodically Deforming Anatomical Structures

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We present a methodology, based on neural paradigms, suitable to analyze periodically deforming anatomical structures and recognize their state. Anatomical structures, considered as 'multimedia objects', are defined as organized sets of images and signals, acquired from multiple sources. These sets are combined and processed using dedicated Artificial Neural Networks to obtain a 3D reconstruction of the object, at different times of its dynamic evolution (deformation cycle). In order to reduce acquisition errors, we consider also an inter-cycle registration of the volumes, resulting in the most likely 3D reconstruction. Morphological and functional characteristics are then associated to each element of the reconstructed volume and processed to discriminate different object states. The developed methodology has been applied to analyze cardiac dynamics and, in particular, to identify physio-pathological states of the left ventricle.

Keywords: Deformation Analysis, Image Registration, Anatomical Structures Classification, Multilevel Neural Networks.

INTRODUCTION

A periodically deforming anatomical structure with pseudo-regular geometry may be represented, by means of suitable diagnostic resources, as a multimedia object, consisting in an organized set of images and signals, describing its non-rigid motion as well as its functional characteristics. The assessment of the state of such complex objects is, therefore, a challenging task and we believe that daily clinical practice and medical research would benefit from automatic analysis methods. Bearing this goal in mind, we consider, from a more general viewpoint, multimedia objects whose motion recurs at regular intervals of time. This specific behaviour is invaluable for obtaining a reconstruction as precise as possible of the object: since multimedia data can be affected by noise or misalignments, it is useful to register the acquisitions performed at the same phases of the deformation cycle and, then, average the corresponding data. In so doing, a statistical dynamic model of the object can be obtained, i.e. its most likely reconstruction at each phase of the cycle.

The methodology, proposed in this paper, exploits the abovementioned consideration and employs advanced neural paradigms for reconstructing an object and identifying its state. In particular, we propose a three-step approach, consisting in: (i) object reconstruction and characterization, (ii) object registration and (iii) state classification.

Among study cases selected to check the efficacy of the developed method, we discuss an application to the evaluation of physio-pathological states of the left ventricle.

1. MATERIALS AND METHODS

Given a class $\mathcal{D}$ of periodically deforming objects, we assume that every element $O \in \mathcal{D}$ can be represented as a sequence $S=(S(t))_{t=1,...,n}$ of $n$ temporal frames, describing a full deformation cycle of the object. Each frame $S(t)$ is defined through a set of synchronous signals and images which allow to get a snapshot of the object in the corresponding deformation phase; more precisely, $S(t)$ consists in a 3D image $I(t)$, representing the object shape, and in a d-dimensional signals vector $f(t)=(f_j(t))_{1 \leq j \leq d}$. 
which supplies global information regarding the object functionalities.

The dynamic behavior of the object, as represented by a frames sequence, is analyzed and exploited to identify the object state by means of a multistage approach consisting in the following three steps:

- **Object reconstruction and characterization**: for each frame $S(t)$, the object volume $V(t)$ is reconstructed by applying neural algorithms to the image sequence $I(t)$ [1]. Morphological features extracted from the images and functional features gathered from the signals vector $f(t)$ are coded into a property function $P(x,t)=(P_1,...,P_m)$ that for each element $x$ of the volume $V(t)$ returns the property vector $(P_1,...,P_m)$, where each $P_i$ represents one of the selected features. The result of this step is the model $(V(t), P(x,t))$ associated to the frame $S(t)$.

- **Object registration**: to eliminate acquisition inaccuracies and obtain the most likely reconstruction of the object, data acquired over multiple cycles can be averaged through an inter-cycle registration, thus obtaining a statistical dynamic model of the object. More precisely, given a collection $\{S_i\}_{1 \leq i \leq k}$ of $k$ frames sequences, acquired at different deformation cycles of the object, the associated models $\{(V_i(t),P_i(x,t))\}_{1 \leq i \leq k}$ are processed in order to get a new model $(W(t),Q(x,t))$, representing the mean shape of the object and its corresponding mean property function [2].

- **State classification**: the statistical dynamic model $(W(t),Q(x,t))$ is further processed to (i) extract shape descriptors and (ii) analyze spatial distribution of the property function. Then, a multilevel artificial neural network (M-ANN) achieves the final classification. Actually, a first level of parallel ANNs modules is developed to classify the temporal evolution of each features class, while a second level ANN supplies the final classification of the object state.

In the following, each step is described in more detail.

**Object Reconstruction and Characterization**

For each frame $S(t)$, the image $I(t)$ is processed to obtain a 3D reconstruction and characterization of the object in the corresponding deformation phase. A dedicated M-ANN architecture is introduced to perform this task, by classifying each voxel in the image domain on the basis of extracted features.

In more detail, a set of local features, obtained applying image processing techniques, is selected and the corresponding feature vector $F(x)$ is associated to every voxel $x$ in the image domain. The set of considered feature should be enough rich to discriminate voxels belonging to the object and may contain feature of different typology (taking into account, for example, voxel position, grey level value and related differential quantities, texture...). The feature vector $F(x)$ is then used as input for the first M-ANN level, which is composed of a set of different classifiers, one for each typology of features. Each classifier is based on an unsupervised Self Organizing Maps (SOM) module and the training is performed with the aim of clustering each input data into crisp classes. The results of the first level are used as input for the final classification, supplied by a single Error Back-Propagation (EBP) module. The output of this last network consists of semantic classes, describing voxel membership to particular structure of the object. Thus, classification of each voxel of $I(t)$ yields a completely defined reconstruction of the object in the form of a dense volume $V(t)$.

Geometric features, describing object morphology, are extracted from the reconstructed volume $V(t)$ together with features regarding density distribution. Besides, functional characteristics are gathered in form of global and local features drawn from the signals vector $f(t)$. All these features are combined in a property vector associated to each voxel of the 3D reconstruction. The characterization can be described as a function $P(x,t)$ that for an element $x \in V(t)$ returns its property vector $\{P_1,...,P_m\}$ consisting in the feature values $P_i$.

**Object Registration**

The periodic motion hypothesis may be exploited to obtain a statistical dynamic model of the object $O$, by averaging data acquired over multiple cycles. Suppose we are a given a collection
State Classification and Recognition

The morphological, densitometric and functional characteristics, coded in \((W(t), Q(x,t))\), are finally used to get the object state classification.

For every fixed phase \(t\) in the deformation cycle, the available data \(\{(V(t), P(x,t))\}_{1≤k}\) are fused by applying the algorithm shown in Fig. 1. A randomly chosen volume among the collection \(\{V(t)\}_{1≤k}\) is selected as reference volume \(W_0(t)\) and every volume \(V(t)\) is elastically registered to \(W_0(t)\). Then, the property functions \(P(x,t)\) \((1≤i≤k)\) are referred to the domain \(W_0(t)\) and averaged, obtaining a new function \(P(x,t)\). Finally, \((W_0(t), P(x,t))\) is warped by the mean of the transformations used in registering the volumes, thus giving an average model \((W_1(t), Q_1(x,t))\). Note that, since registration algorithms are prone to concatenation error, \((W_1(t), Q_1(x,t))\) may be biased by the choice of the reference volume \(W_0(t)\). If needed, it is possible to get rid of this bias using an iterative method: we simply repeat the aforementioned registration and averaging procedure, using the mean volume \(W_n(t)\), obtained at the \(n\)-th step, as reference volume in the \((n+1)\)-th step. A discussion about the convergence of this algorithm can be found in [2].

At the end, we obtain, for each phase \(t\), the statistical dynamic model \((W(t), Q(x,t))\) that represents the most likely reconstruction and characterization of the object in the corresponding deformation phase.

\[
\begin{align*}
\text{Object Registration} & \\
& i = \text{rand}(k) \\
& W_0(t) = V(t) \\
& \text{Do } \{ (n=0, n++) \} \\
& \quad \text{For } (j=1, j≤k, j++) \\
& \quad \quad T_j := \text{Registration}(W_n(t) \rightarrow V_j(t)) \\
& \quad P(x,t)=1/k \sum_j P(T_j(x,t)) \\
& \quad T := \text{AverageTransform}(T_j \mid j=1, \ldots, k), \\
& \quad W_{n+1}(t) = T(W_n(t)) \\
& \quad Q_{n+1}(x,t) = P(T^{-1}(x,t)) \\
& \quad \text{If } \text{Similarity}(T, \text{Identity}) > \delta \text{ then} \\
& \quad \text{Return } (W(t), Q(x,t)) \\
& \}
\]

Fig. 1. The registration algorithm.

\[\{S_i\}_{1≤k}\] of \(k\) frames sequences and let \((V(t), P(x,t))_{n=1,2,\ldots,n}\) be the associated models.
\( \mathcal{F}(t) (t=1,\ldots,n) \) of its features class and classify its dynamic behaviour.

Each module is based on a SOM architecture, which discovers how the data spontaneously group to form coherent clusters of object deformation modes. The output of the first level is then passed to the second (decisional) level, achieving the final state classification. This final module is realized as a Multilayer Perceptron trained according to the Error Back-Propagation algorithm.

Decomposing the entire state classification task into two steps and mapping these decomposition onto a multilevel ANN we obtain several advantages. Actually, allocating different ANNs to the key actions of the entire process allows each network to specialize itself in solving the respective problem. This can be seen in terms of learning speed, generalization and representation capabilities [3]. In other words, a multilevel ANN behaves more robustly, more efficiently, and can also generalize better than a single neural network.

2. A STUDY CASE: MRI HEART DYNAMICS

As study case, we considered the analysis of the cardiac dynamics and, in particular, the identification of physio-pathological states of the left ventricle (LV).

Five cardiac cycles \((k=5)\) have been imaged by using a Magnetic Resonance (MR) scanner. For each cycle, 30 frames \((n=30)\), consisting of 11 2D slices, were acquired at a 30 ms rate. An ECG signal has also been measured to gate MR acquisitions.

Fig. 2 shows one of the images used for the segmentation and the result of the 3D reconstruction step through the dedicated ANN. Ventricular surfaces \((i.e.\, epicardium\, and\, endocardium)\) have been extracted and used in the subsequent steps.

![Fig. 2. An example of (left) a segmented MRI slice of the LV and (right) 3D reconstruction.](image)

For the characterization task, from the MR and ECG investigations, we extracted a set of physical characteristics, regarding the geometric and morpho-functional properties of the LV. More precisely we associated to every boundary voxel the following features [4]:

- Intensity measured as grey level value.
- Position measured as coordinates w.r.t. a cylindrical reference system along the long axis of the ventricle.
- Wall thickening. This value has been estimated using the centreline method: we considered the ray in the aforementioned cylindrical reference system passing through the voxel under examination and computed the length of its intersection with the myocardium.
- Principal curvatures. Estimation of curvatures in a boundary point as been obtained by fitting a quadratic surface patch in a neighbourhood of the point.

After the registration step, we obtained the statistical dynamic model of the LV and supplied it to the multilevel ANN for the state classification.
For this final step, we have considered simple shape descriptors (namely parameters of a quadratic surface fitting for epicardium and endocardium) as well as sampling of the properties function on regularly spaced rays. Classical functional parameters, such as left ventricular cavity and myocardium volume, have also been included.

This set of features has been used in a first validating test of the described methodology in the highly complex setting of cardiac dynamics.

CONCLUSION

In this paper, we have proposed a methodology, based on neural paradigms, for the analysis and classification of the state of periodically deforming objects. Three successive steps are considered for (i) reconstructing and characterizing the object in each frame of its deformation cycle, (ii) registering the frames of different cycles (iii) classifying the state of the object.

As a preliminary result we discussed an application to the evaluation of physio-pathological states of the left ventricle.

In the future further improvements are possible; performing motion estimation, for example, may lead to the definition of other features, such as strain tensor, and to a more accurate estimation of current parameters.

REFERENCES