A&QT-R 2002 (THETA 13)
International Conference on Automation, Quality and Testing, Robotics
May 23 – 25, 2002, Cluj-Napoca, Romania

FEED–FORWARD ASSOCIATIVE NEURAL NETWORKS FOR 3-D IMAGE PROCESSING, RECONSTRUCTION AND MODELLING IN CORONARY ARTERIES

TIBERIU COROESCU (1), SILVESTRU CONSTANTIN (2), MIRELA-MARIA COROESCU (3),

(1) - Control and Industrial Informatics Department - University of Petrosani. Present Address: Str. Cetatea Histria nr. 3, Bl. M14, Sc. B, Ap. 53, Sector 6, Bucuresti. E -mail: corot@bx.logicnet.ro

(2) - Radiology and Medical Imaging Department – Clinical Central Military Hospital Bucharest, Present Address: Str. Washington nr. 18, Ap. 2, sector 1, Bucuresti. E-mail: B98ACS@HOTMAIL.COM

(3) - Radiology and Medical Imaging Department – Clinical Central Military Hospital Bucharest, Present Address: Str. Cetatea Histria nr. 3, Bl. M14, Sc. B, Ap. 53, Sector 6, Bucuresti. E-mail: corot@bx.logicnet.ro

Abstract. The paper analyses the impact of neural networks on Image Processing, Image Reconstruction and Image Modelling in Three-Dimensional 3-D using Biplane 2-D incomplete X-Ray Projections data in order to apply it to Coronary Arteries. It is emphasized the new application to reconstruct a sequence of cross sectional shapes along an arterial segment and to position them accurately in 3D space. The paper presents based on the principle of computed tomography CT the practical algorithm 3DSCT for mapping a reconstructed arterial cross section onto its sectional slice for estimating the blood vascular cross sectional shape from its two orthogonal projections. A new application of feed-forward associative neural networks in medical imaging is proposed, based on their proprieties of pattern recognition using the huge information furnished now by Picture Archiving and Communication Systems PACS.

Keywords: Neural Networks, Image Processing, Image Reconstruction, Image Modelling, Medical Imaging

1. INTRODUCTION

Over the past two decades the concept of processing and reconstruction appeared very frequently in the literature of medical imaging and digital image analysis techniques. It was used in different contexts with two different meanings. As an *image reconstruction* from projections, it was defined on the basis of Radon-transform and also called a *tomographic scan*.

A typical example of a reconstruction in such a way is computed tomography CT scanning. The image reconstruction in this case is in fact a 2D transform, which defines a mapping from the image space to the projection space and vice versa. In the discrete case, both spaces are discrete and have a finite number of dimensions. An image reconstruction problem may be more generally viewed as to search for a mapping from a R-dimensional projection space (of size “m+n”) to S-dimensional image space (of size “mxn”). A unique mapping is only possible by constraining the solution space to a subset of the entire S-dimensional space.

In the case of X-ray CT , a 3D reconstruction can be formed by scanning successive cross sectional slices within an object and stacking the resulting 2D reconstructions. This forms another class of the general reconstruction problem, having the goal to arrive at the 3D-shape of an object, or in other words at its outer surface, and then to display it with computer graphics techniques.

A set of 2D sectional reconstructions is stacked one above the other in the positions determined with the scanning geometry. This is known as a registration of an alignment of images in 3D space. By extracting outer contours of the object within each slices, they are assumed to constitute a *3D envelope mesh* of the real object. With 3D reconstruction techniques we want in fact to estimate a surface based on the supporting mesh, which should approximate the real outer surface of the object to be reconstructed as accurate as possible.

In general, 3D graphics reconstruction is based upon a given set of parallel 2D topographic scans, where the distance between them is usually larger than the distance between pixels in the slices named anisotropic spatial resolution. In fact, in the case of parallel slices, the distance between two successive cross sections named slice distance determines the spatial resolution of the modelling in the third dimension. The spatial resolution of the other two dimensions is defined by the tomographic scan sampling.

Therefore, the 3D reconstruction is actually defined in a sense of a spatial interpolation, which is based on the assumption of the geometric continuity of the anatomic objects. The 3D shape is interpolated from a supporting mesh consisting of a finite number of vertices. In contrary to image reconstruction it is called *graphics reconstruction* because mainly computer graphics techniques are involved.

The simplest approach to the graphics reconstruction is either the triangulation, which connects all of the mesh vertices with the triangles and uses these triangles to approximate the local real surfaces, or the volume stacking, which divides an object in an appropriate way into a set of voxels uniquely included in or excluded from the object. In fact, a wire-frame display of the triangulated surface model gives an evidence of the human ability to reconstruct the 3D shape from a supported mesh. In practice, the 3D graphics reconstruction is applied as a visualization tool of the image reconstructions by creating a 3D geometric model of the real object from its sectional scans, having the name of *3D modelling process.*

In a preliminary stage of reconstruction imaging, aggregate (global) dates are gathered by measuring a signal issued by a large selected volume. The construction stage consists then in extraction through informatic calculus from global dates, of punctual dates corresponding to voxels of volume. The extraction of voxels' relative dates is possible only by codifying them before extraction.

In the first phase, are realized the cross-sections having the same spatial resolution into the three directions of the space and containing the vascular information in 2-D or 3-D. The axis of stacking for cross-sections has the to be parallel with the examined vessels.

In the second phase, is realized the reconstruction by selecting the intravascular voxels in every precedent cross-sections and by projecting them on a plan parallel with the axis of stacking cross-sections.

The selection of the intravascular voxels depends of the modality in which will be processed information in line with blood flowing. The powerful noninvasive techniques Magnetic Resonance Angiography MRA and Computed Tomography Angiography CTA can visualize abdominal vessels accurately [8], [9], [10], [12]. Introduction of contrast-enhanced spiral CT several years ago greatly increased the appeal of CT for vascular imaging. Technique is relatively simple, based on differences in density only, and is therefore quite robust. Multislice technology in CTA enables large volumes to be imaged with a single breath-hold at unmatched spatial resolution. The submillimeter isotropic voxels imaged allow data reformatting during postprocessing, adding real diagnostic value in clinical practice [2], [3], [9], [12].

2. MEDICAL IMAGE PROCESSING, RECONSTRUCTION AND MODELLING

The coronary arteries will be processed, reconstructed and modelled with their supporting mesh, which consists of the outer contours of arterial cross sections distributed along their centerlines. In order to create a 3D model of coronary arteries in such a way, 3D coordinates of the arterial cross sections reconstructed in a binary matrix must be computed. In fact, this problem has been solved with the following epipolar relation which determines the related sectional slice [3]:

$$\mathbf{n} = \mathbf{a_1} \times \mathbf{a_2} \qquad (1)$$

where $\mathbf{n}$ is the normal of the slice and $\mathbf{a_1}$ and $\mathbf{a_2}$ are the direction vectors of the rays of two points $\mathbf{p_1}$ and $\mathbf{p_2}$ of the arteries from two orthogonally projected images $\mathbf{I_1}$ and $\mathbf{I_2}$. This relation can be used to compute the normal vector $\mathbf{n}$ of the sectional slice and pointed out that its center $\mathbf{p}$ reconstructed from a pair of central points ($\mathbf{p_1}$, $\mathbf{p_2}$) on the pair of epipolar scanlines may be used as a base-point of the slice. To position an arterial cross section on the slice, however, its freedom of rotation around the normal vector remains to be determined.

The rotation freedom can be determined by relating the local planar system ($\mathbf{X_p}$, $\mathbf{Y_p}$) for the sectional reconstruction to the rays $\mathbf{a_1}$ and $\mathbf{a_2}$ of the corresponding centerline points $\mathbf{p_1}$ and $\mathbf{p_2}$, which define the slice. To represent an arterial cross sectional shape in 3D space, the normal vector direction of the slice is added to the planar system as the third coordinate axis $\mathbf{Z_p}$. In the new system ($\mathbf{X_p}$, $\mathbf{Y_p}$, $\mathbf{Z_p}$) the sectional slice is defined as the plane with $\mathbf{z_p = 0}$. Because the X-ray beams of biplane X-ray system are actually not parallel, the rays $\mathbf{a_1}$ and $\mathbf{a_2}$ are not perpendicular to each other, even if two projections are strictly orthogonally recorded. So the scalar product of the two rays $\mathbf{a_1}$ and $\mathbf{a_2}$ is generally not zero:

$$\mathbf{a_1} \cdot \mathbf{a_2} \neq 0 \qquad (2)$$

One of the two rays, say $\mathbf{a_1}$, is taken to be the X_p-axis of the local coordinate system and the Y_p-axis within the slice can be defined perpendicular to $\mathbf{a_1}$ and passing through the center $\mathbf{p}$. The local system is originated at the base point $\mathbf{p}$ of the slice and its unit vectors $\mathbf{x_p}$, $\mathbf{y_p}$ and $\mathbf{z_p}$ in the axial directions are defined with the following equations:

$$\begin{aligned} \mathbf{x_p} &= \mathbf{a_1} / | \mathbf{a_1} | \\ \mathbf{y_p} &= \mathbf{a_1} \times (\mathbf{a_1} \times \mathbf{a_2}) / | \mathbf{a_1} \times (\mathbf{a_1} \times \mathbf{a_2}) | \qquad (3) \\ \mathbf{z_p} &= \mathbf{a_1} \times \mathbf{a_2} / | \mathbf{a_1} \times \mathbf{a_2} | \end{aligned}$$

The sectional slice is then related to the world coordinate system ($\mathbf{X\ Y\ Z}$) with the following coordinate transforms:

$$\mathbf{p} = \mathbf{p_p} \cdot \mathbf{T_R} \cdot \mathbf{T_T} \qquad (4)$$

where $\mathbf{p}$ and $\mathbf{p_p}$ are points in the local system ($\mathbf{X_p}$, $\mathbf{Y_p}$, $\mathbf{Z_p}$) respectively the world system ($\mathbf{X, Y, Z}$) with homogeneous coordinates, and $\mathbf{T_R}$ and $\mathbf{T_T}$ are the rotation and the translation transformation, respectively. The transformation $\mathbf{T_R}$ is given by a rotation of the local system around the origin of the world system, that is:

$$\mathbf{T_R} = \begin{pmatrix} \mathbf{l_1} & \mathbf{m_1} & \mathbf{n_1} & \mathbf{0} \\ \mathbf{l_2} & \mathbf{m_2} & \mathbf{n_2} & \mathbf{0} \\ \mathbf{l_3} & \mathbf{m_3} & \mathbf{n_3} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \end{pmatrix} \qquad (5)$$

where $(\mathbf{l_i} \;\; \mathbf{m_i} \;\; \mathbf{n_i})^T$, i = 1,2,3 are the components of the unit vectors $\mathbf{x_p}$, $\mathbf{y_p}$ and $\mathbf{z_p}$, that is:

$$\mathbf{x_p} = (\mathbf{l_1} \;\; \mathbf{m_1} \;\; \mathbf{n_1})^T$$
$$\mathbf{y_p} = (\mathbf{l_2} \;\; \mathbf{m_2} \;\; \mathbf{n_2})^T \qquad (6)$$
$$\mathbf{z_p} = (\mathbf{l_3} \;\; \mathbf{m_3} \;\; \mathbf{n_3})^T$$

The transformation $\mathbf{T_T}$ is simply a translation from the origin to the base point **p** of the slice:

$$\mathbf{T_T} = \begin{pmatrix} \mathbf{1} & \mathbf{0} & \mathbf{0} & \mathbf{x} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{y} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{z} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \end{pmatrix} \qquad (7)$$

where the translations are given with the 3D world coordinates of the slice's base **p**:

$$\mathbf{p} = (\mathbf{x} \;\; \mathbf{y} \;\; \mathbf{z} \;\; \mathbf{1})^T \qquad (8)$$

The algorithm for mapping a reconstructed arterial cross section onto its sectional slice named **3DSCT** can be now constructed in following 4 steps:

Step 1. Detect the outer contour of a cross section from the reconstructed binary matrix and denote the contour $\mathbf{Cont_{ij}}$, as a sequence of pixels (**i,j**).

Step 2. Translate the row-column coordinates **(i,j)** to the local coordinate system ($\mathbf{X_p}$, $\mathbf{Y_p}$, $\mathbf{Z_p}$) using the relations:

$$\mathbf{z_p = 0}$$
$$\mathbf{x_p = j - (n+1) / 2} \qquad (9)$$
$$\mathbf{y_p = (m+1) / 2 - i}$$

Step 3. Compute the directional vectors of the local system $\mathbf{x_p}$, $\mathbf{y_p}$ and $\mathbf{z_p}$ with the coordinates of two rays defining the sectional slice according to equations (3).

Step 4. Use the transforms from equation (4) with the matrices $\mathbf{T_R}$ as in equation (5) and $\mathbf{T_T}$ as in equation (7) in order to map the local coordinates $\mathbf{p_p}$ into the world coordinates **p.**

The implementation of this mapping algorithm was realized using the feed-forward associative neural networks described into the next section.

3. FEED-FORWARD ASSOCIATIVE NEURAL NETWORKS

Neural networks represent networks of adaptable nodes which, through a process of learning from task examples, store experiential knowledge and make it available for use. The process of storing experiential knowledge can be understand using the simplest device called Toy Adaptive Node TAN [1], [4], [13], [16], [17].

There are N inputs labeled X1, X2, …, XN, and one output F. The actual 0 and 1 values present at the input will be referred to as an input bit pattern.

The function of the node may be shown as a truth table, that is a table showing what F will be for each of the possible patterns of 0s and 1s that can occur at the inputs [8], [9].

The node may operate in two modes: it can be taught (during which time its function can change) or used (during which time it cannot change). Which of these modes it operates in is determined by setting the T/U terminal to 1 for teaching or to 0 for using.

While teaching, the node associates whatever is present (0 or 1) at the teaching input T with whatever pattern is present at the inputs terminals. This means that whenever that particular input pattern occurs again in a subsequent using phase, the learnt or associated output symbol (0 or 1) is at output F.

For node TAN can be introduced an undefined output labeled “0/1”, that is this node outputs a 0 or a 1 chosen at random. This condition exists either if the particular input has not been taught at all, or if there is some sort of confusion about the desired output for a particular input. For example, if the node is taught to output a 1 in response to a particular input pattern and is then taught to output a 0 in response to the same pattern, the output will be undefined.

A feed-forward TAN network has associative properties and may consists of three TANs labeled T1, T2, T3 [1], [8], [14]. It is intended to train it in line with such a firing rule to recognize a T-shaped pattern at a matrix of inputs from X11 till X33 by causing the three TANs to fire at their outputs F1, F2 and F3. Also, an H-shaped input pattern trains the net not to fire at F1, F2, and F3.The truth tables for the three TANs are presented in tables 1, 2, and 3 [8], [9].

Truth table for TAN 1 Table 1

Pattern						H		T
X11	0	0	0	0	1	1	1	1
X12	0	0	1	1	0	0	1	1
X13	0	1	0	1	0	1	0	1
F1	0	0	1	1	0	0	1	1

Truth table for TAN 2 Table 2

Pattern			T					H
X21	0	0	0	0	1	1	1	1
X22	0	0	1	1	0	0	1	1
X23	0	1	0	1	0	1	0	1
F2	1	0/1	1	0/1	0/1	0	0/1	0

Truth table for TAN 3 Table 3

Pattern			T			H		
X31	0	0	0	0	1	1	1	1
X32	0	0	1	1	0	0	1	1
X33	0	1	0	1	0	1	0	1
F3	1	0	1	1	0	0	1	0

In order to predict the output pattern for any given input patterns, the above truth tables are applied. For a test pattern which supplies inputs X11X12X13=010 to TAN 1, is generated 1 at F1 (in line with table 1), while F2 and F3 are the same as for the “T” training pattern, because for inputs 010 to TAN2, the output F2=1 (in line with table 2), and for inputs 010 to TAN 3, the output F3=1 (in line with table 3).

2. CONCLUSIONS

In the paper is presented for Coronary Arteries a new application of reconstruction the sequence of cross sectional shapes along an arterial segment from Biplane 2D incomplete X-Ray Projection data.

The practical algorithm 3DSCT implemented in four steps for mapping the reconstructed arterial cross section shape onto its sectional slice is deducted.

The paper emphasizes the perspective of feed-forward associative neural networks in medical imaging, based on their capabilities of pattern recognition and competitive learning using the recent easy access of huge medical information furnished by Picture Archiving and Communication Systems PACS [2].

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