AN ARTIFICIAL NEURAL NETWORKS ALGORITHM FOR PATIENT POSITIONING IN BREAST CANCER RADIOTHERAPY

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Abstract: An Artificial Neural Networks (ANNs) based method, for the automatic and real-time optimization of patient set-up in breast cancer radiotherapy, is proposed. With respect to commercial passive marker-based systems and constrained surface registration procedures, the proposed ANNs algorithm was designed to detect and correct patient misalignments by using laser spots projected on breast surface as fiducial points. The method features generalization capabilities related to inter-session and intra-session modifications of the irradiation target. The technique was validated through simulation activities, based on clinical data, with great adherence to the clinical scenario. Results show that both the non-deterministic nature of ANNs and the model-specific training modalities ensure great generalization capabilities of the algorithm, compared to the other repositioning methods, leading to a high reliability in patient positioning correction: median±quartile measures of 3-D displacements, affecting the whole set of control points, were reduced from the initial value of 9.86±5.26 mm up to 3.01±2.60 mm.

Introduction

The most important challenge in radiotherapy treatments is to accurately deliver a specific dose of radiation to a predefined target volume. This can be achieved only with the precise positioning of the patient, during each therapy session, with respect to the radiotherapy system.

Conventional methods for patient repositioning and immobilization are mainly based on laser centering lines, skin tattoos and personal frame systems; nowadays, optoelectronic techniques are available in clinical practise to monitor, in real-time, the location of external fiducials, which are light reflecting passive markers, on the patient treating area. The position correction requires the minimization of the current marker configuration with respect to a corresponding reference one. As drawbacks, these methods require 7-8 markers at least: consequently, it is necessary to spend time in order to accurately replace the control points on the patient's skin, at each therapy session. Moreover, they are based on the strong assumption that the internal structures are stiffly connected with the external surface, thus do not considering the effects of organ motion due to the breathing movements.

Recently, new techniques based on the detection of the entire irradiated body area have been proposed in order to account for surface morphological changes [1,2] and to increase the number of control points. Other methods are based on the acquisition of under sampled surface by using laser spots projected on the patient skin [3,4]. In this case two passive markers are used to guarantee the convergence of the registration algorithm.

In this paper, a non deterministic method based on Artificial Neural Networks (ANNs) is described. The technique implies the use of only laser spots as surface control points as if they were passive markers, but without requiring the presence of real fiducial passive markers, thus reducing time and errors related to markers replacement on selected skin landmarks. Moreover its non-deterministic nature allows the correction of the errors due to patient's breathing movements.

The method was tested through simulated activities reproducing the typical clinical conditions.

Materials and Methods

The breast surface model was obtained from the CT of the treatment planning system.

CT data (5 mm slice thickness) of 4 subjects, enrolled in this study and treated for breast cancer radiotherapy at the *Istituto Europeo di Onclogia* (IEO, Milan), were processed with a commercial software (Amira™ 3.1.1, TGS Inc.), in order to reconstruct breast surface models. A threshold, based on the Hounsfield scale, was used by the marching cubes algorithm [5] to build the iso-surface corresponding to the patient's external body surface; a detailed surface model was generated in this way and it was typically composed of 10000-15000 triangles per model.

Two CT scans of one patient treated for left breast carcinoma, acquired in free breathing (FB) and deep inspiration breath hold (DIBH) conditions, were registered and processed (see figure 1) in order to evaluate the radial surface displacement due to the

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patient breathing. Analyzing these data, a geometrical surface deformation tool was implemented to mimic intra-session target motion and deformation. The algorithm was developed in MatLab® environment (MatLab® version 6.5, The MathWorks, Natick, MA) and it was applied to each model.

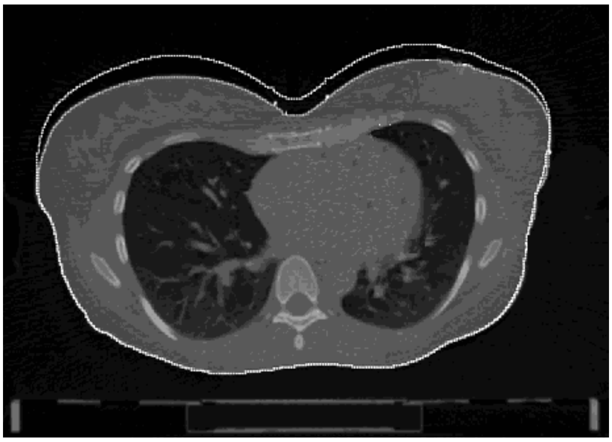

Figure 1: FB and DIBH CT slices registration

The configuration of laser spots on the surface was defined by means of a simulated experimental set-up of 10 laser beams. The generated laser spots in reference conditions (*Virtual Markers*, *VMr*) were considered solid with the 3D surface and used as verification points for the evaluation of the neural algorithm performances (see figure 2).

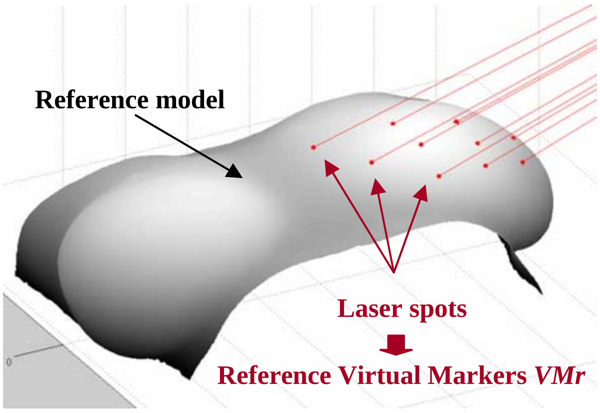

Figure 2: The reconstructed model and the simulated laser spots for reference dataset

A set of 10 Artificial Neural Networks (one for each laser spot) was trained. The nets inputs were the current laser beams intersections (*lc*) with the surface model, while the nets outputs were the current 3D coordinates of *Virtual Markers* (*VMc*).

Every net was a multilayer perceptron with a single hidden layer of 24 neurons (see figure 4). The output layer was made by 3 neurons, one for each cartesian coordinate (X, Y and Z) of each *VMc.* The networks were organized in a cascaded-forward architecture: the first layer had weights coming from the input; each subsequent layer had weights coming from the input of all previous layers.

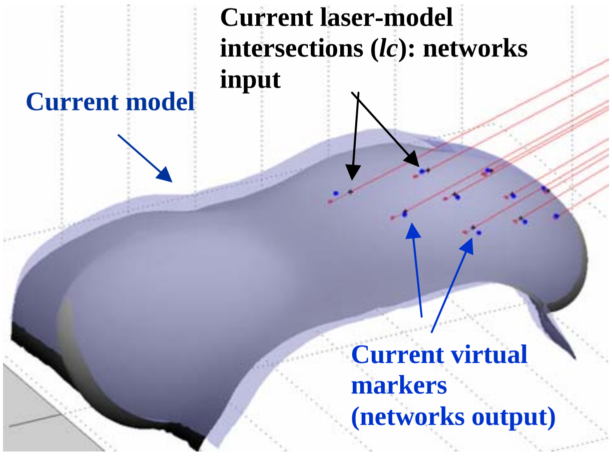

Figure 2: Misalignments surface model (current model) and nets INPUTS/OUTPUTS

The network training function updated the neurons weight values according to the Levenberg-Marquardt optimization algorithm [6].

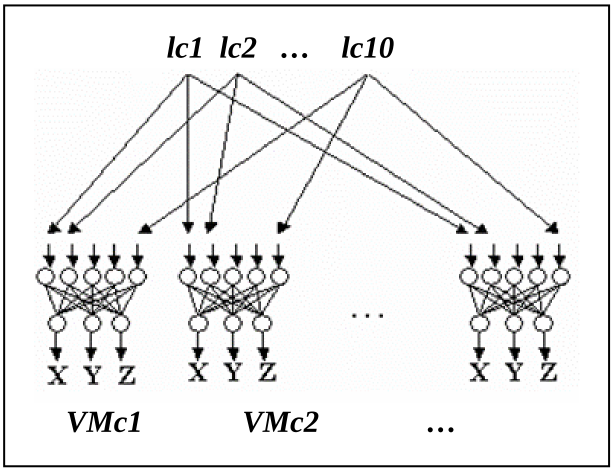

Figure 3: Networks architecture

The ANNs training dataset was generated by applying 2000 random 6-dofs rototranslations to the reference surface model. Range of linear and angular displacement was ±10 mm and ±6°.

For each model, two training dataset were generated: in the first case, no model deformations were considered (*undeformed* training), in the second case, 8 breathing deformation patterns were included in the training procedure (*deformed* training), simulating patient respiration from deep expiration to deep inspiration. Non-rigid deformation ranged from – 8mm to 12 mm with respect to the mean respiration level. With the same modalities testing dataset was generated (*undeformed* testing and *deformed* testing).

In order to simulate patient position correction the ANNs output was fed to an iterative procedure, which was designed to estimated the best set of roto-translation corrective movements (in a least-squares sense) for the

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minimization of the displacements between reference and ANNs predicted current *Virtual Markers*.

The networks performances were evaluate by computing the *root mean square error* between the desired and the networks estimated outputs. The model position correction after the application of minimization procedure was checked by calculating the residual errors on the estimated *VMc*. Non-parametric statistical tests were applied (Wilcoxon signed rank test).

Results

In table 1 and in table 2 RMSE values are showed for *undeformed* and *deformed* testing.

Table 1: Root mean square error between desired and nets estimated outputs when non morphological changes are considered.

	Patient 1	Patient 2	Patient 3	Patient 4
RMSE [mm]	1.13	2.26	1.64	0.99
RMSEs[mm]	0.13	0.08	0.12	0.08
RMSEr[mm]	1.12	2.25	1.62	0.98

Root mean square error was decomposed in its random (RMSEr) and systematic (RMSEs) component, being this latter related to possible algorithm bias, as described Willmott *et al.* [7].

Under *undeformed testing* conditions, the systematic component of RMSE resulted always less than the random one: the maximum value was 0.13 mm for patient 1.

In the case of *deformed testing*, worst result were found only for patient 4 when maximum expiration and inspiration conditions were simulated.

Table 2: Root mean square error between desired and nets estimated outputs when surface model deformation is considered.

Patient	Model Err [mm]	Expir.	Mild Expir.	Mean Resp.	Mild Inspir.	Inspir.
1	**RMSE**	1.88	1.35	1.07	1.07	1.35
	RMSEs	0.75	0.46	0.20	0.17	0.50
	RMSEu	1.73	1.28	1.05	1.05	1.25
2	**RMSE**	2.37	1.87	1.71	1.65	1.82
	RMSEs	1.08	0.43	0.27	0.25	0.49
	RMSEu	2.11	1.82	1.69	1.63	1.76
3	**RMSE**	1.93	1.39	1.33	1.43	1.66
	RMSEs	0.63	0.24	0.13	0.33	0.59
	RMSEu	1.83	1.37	1.32	1.39	1.55
4	**RMSE**	2.84	1.44	0.93	0.94	1.50
	RMSEs	2.40	1.06	0.38	0.40	1.16
	RMSEu	1.51	0.97	0.85	0.85	0.95

Efficiency of the whole methodology in detecting and correcting position, after the application of the patient corrective parameters estimated by the least-squares iterative procedure, was tested.

Figure 4 shows *median±quartile* values, computed on the 100 testing examples, of initial and residual 3-D displacements affecting control points of patient 2 and patient 4, which were the worst and the best case respectively for *undeformed* testing.

In figure 5 results concerning *deformed* testing datset are plotted. Wilcoxon signed rank test for pair data confirmed significant 3-D displacements reductions for virtual markers with $p<1e-6$.

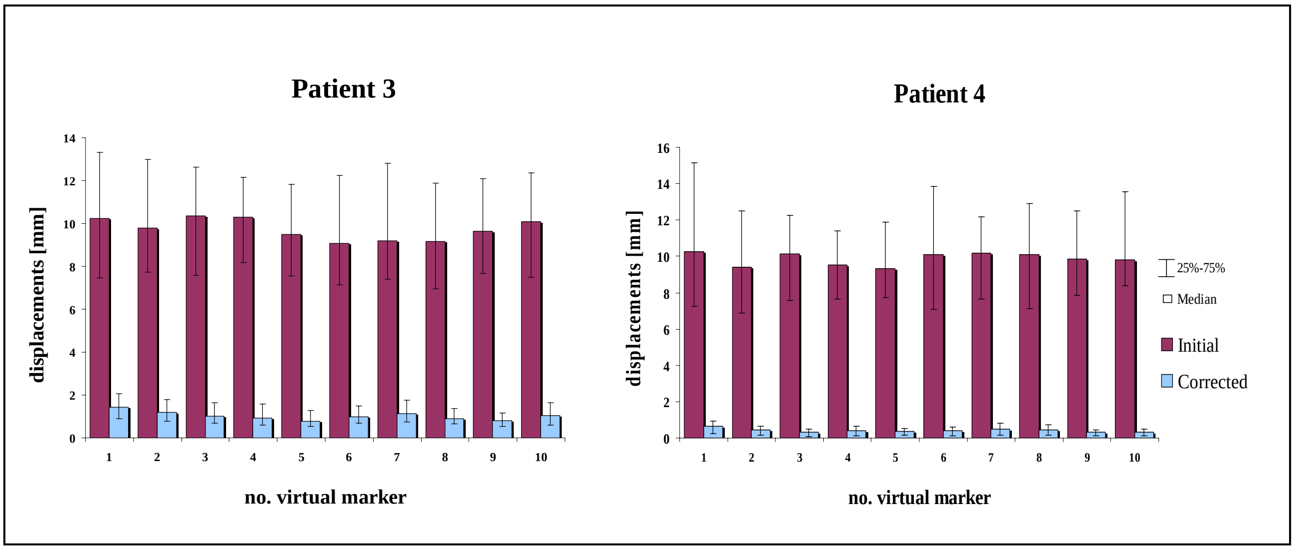

Figure 4: Comparison between 3-D initial and residual displacements affecting the virtual markers estimated by networks (*undeformed* testing dataset).

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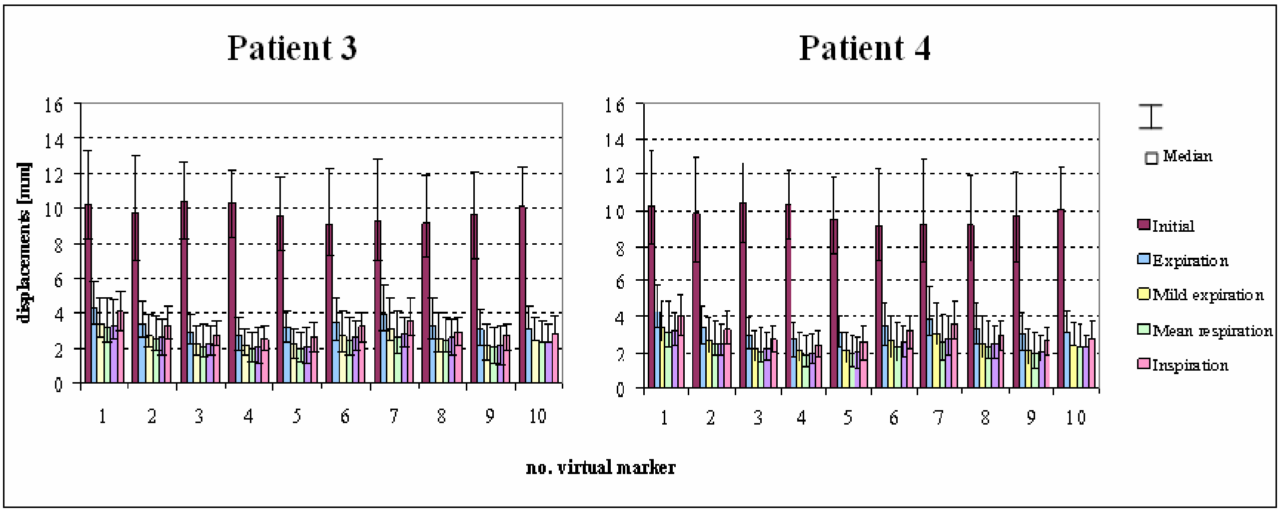

Figure 5: Comparison between 3-D initial and residual displacement affecting the virtual markers estimated by networks for different breathing levels (*deformed* testing dataset).

Discussion

In this paper an original ANNs procedure, for patient positioning in radiotherapy, is proposed. The method represents an innovative and efficient trade-off between position control techniques based on physical passive markers [8] and technologies based on anatomical surface detection and registration by means of thousands of light spots [2].

The technique was tested by simulating the detection and the correction of misalignments of four 3D surface models built from real CT data. Morphological surface model deformations were included in the networks training dataset, in order to assess the generalization capabilities of the algorithm.

The principal aim of the described methodology was to predicted, at each therapy session, the position of the current verification points, which were laser spots acquired only at the treatment planning time, as they were solid with the surface. Then, a least-squares iterative procedure was applied to perform the registration between the reference point configuration and the current-estimated one, in order to obtain patient position corrective parameters. Since the *virtual markers* were laser spots projected on the patient treated area, their number could easily increase, without interfering with the clinical practice and guarantying better registration performance.

Results confirm the great generalization capabilities of the algorithm in estimating current virtual markers location. This is valid, even when non-rigid surface deformations, simulating patient breathing effects, are included. The method turns out to be flexible, in terms of control point number, and provides real-time output after ANNs training.

Conclusions

We can conclude that the proposed technique represents a competitive alternative to surface registration procedure and patient position control based on passive markers. The next step will be to test the efficiency of the method for the clinical application to definitely validate the entire procedure.

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