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An Assessment on Implementation of Imperialist Competitive Algorithm for Motion Dataset Optimization at Radiotherapy with External Surrogates

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ABSTRACT

Introduction: One of the most important components in radiotherapy with external surrogates is utilizing consistent correlation model to estimate tumor location as model output on the basis of external markers motion dataset. In this study, imperialist competitive algorithm (ICA) was proposed to process and optimize motion dataset for correlation model. The simplicity of correlation model based on this algorithm may result in less targeting error with the least computational time.

Material and Methods: A correlation model based on adaptive neuro-fuzzy inference system (ANFIS) was utilized with database of 20 patients treated with CyberKnife Synchrony system. In order to assess the effect of proposed data optimization algorithm, two strategies were considered. The correlation model was used with and without implementing ICA. Then, targeting error of ANFIS model was compared at two strategies using statistical analysis.

Results: The results showed that implementing the proposed algorithm on ANFIS model could remarkably improve the performance accuracy of ANFIS correlation model by eliminating unnecessary and noisy inputs and making the model simpler. Moreover, model simplicity factor could highly reduce model computational time, which is attractive for clinical practice.

Conclusion: ICA was proposed as data optimization algorithm on motion dataset of patients treated with external surrogates' radiotherapy. Our proposed algorithm could highly optimize the input motion dataset of correlation model for estimating tumor position by selecting enough data points with high degree of importance. The final results showed an improvement of targeting accuracy of correlation model, as well as a significant reduction at model computational time.

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Introduction

One of the most important issues at external beam radiotherapy is delivering a prescribed 3D uniform dose to the target volume while minimizing damage to the nearby healthy tissue. This issue becomes more serious while tumor moves irregularly due to intra-fractional motion mainly caused by breathing phenomenon in the thorax region of patient body [1]. From mathematical point of view, tumor motion can be in translation, rotation, deformation, separately or even in a combination of these dynamics modes [2-8]. In modern precise radiotherapy, several efforts have been proposed to manage the effect of motion error on treatment process known as breath-hold, motion-gated radiotherapy, and real-time tumor tracking radiotherapy (RTRT) [4, 9-15]. The latter case is under research and other strategies are being clinically implemented. Breath holding is on the basis of patient cooperation and has some non-negligible errors during therapeutic beam irradiation.

In motion-gated radiotherapy, tumor motion is monitored and target volume is irradiated in pre-defined phase of breathing such as end of exhalation, while gate is activate in clinical application [4, 14, 16-17]. External surrogates' radiotherapy and fluoroscopy-based radiotherapy are two common treating systems against conventional radiotherapy that use additional hardware and software tools for tumor motion monitoring [18,19]. At external surrogate's radiotherapy, external motion of thorax and abdomen regions and internal motion of tumor are gathered as external-internal datasets. Then, a correlation model is built using this dataset to correlate external thorax motion with tumor motion at pre-treatment phase few minutes before treatment. After model construction, it is ready to infer tumor motion as model output by means of external motion data points during treatment. Moreover, the correlation model performance is checked periodically during treatment and its parameters are updated by using new external-internal data point, taken by monitoring systems. It should be noted that external surrogates' radiotherapy gives lower dose to

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the patients that results lower side-effects according to the concept of As Low As Reasonably Achievable (ALARA) principle [20]. Several linear and non-linear correlation models have been proposed to estimate tumor position mathematically. Some of these models were taken into account in our previous studies considering their pros and cons, optimum location of external surrogates, and even using marker-less strategies comprehensively [21-28].

Apart from the structure and robustness of each correlation model, its performance depends highly on the quality and quantity of external-internal dataset. This study aimed to assess the inherent properties of dataset responsible for model construction and model performance during treatment. To do this, a proper data selection algorithm was taken into account to yield an optimized correlation model for RTRT.

In this study, we focused on adaptive neuro-fuzzy inference system (ANFIS) as correlation model since its abilities were proved in our previous studies. In fact, the reasoning capabilities of fuzzy inference systems and learning skills of neural networks are combined together in a unique system known as ANFIS [29-31].

The configuration and performance of ANFIS correlation model highly depends on the number and importance degree of data points as one member of external-internal dataset. Therefore, a data pre-processing algorithm is required to select the optimum and useful dataset to find a compromise between model performance and its complexity caused by excessive number of inputs.

An input selection algorithm would be beneficial to give optimum and useful data as input for our ANFIS model. Moreover, the simplicity of prediction model results in less computational time for model re-construction during each update; therefore, tumor tracking is done in real-time mode that is highly necessary in clinical application.

The purpose of this study, is design and implementing an optimization algorithm called imperialist competitive algorithm (ICA) to choose the best combination of inputs for each dataset. The selected inputs result in the least prediction error at the minimum run-time. ICA is an optimization algorithm which commences to work with an initial community of countries. These community individuals are divided into two categories, imperialists and colonies. The imperialists are countries which have the most power, the least cost, and can seize more colonies based on their power. In our optimization problem, imperialists are the combination of inputs that lead to lower errors of the correlation model. The rest of the countries (the colonies) and imperialists altogether shape empires. The contest among empires to seize more colonies is the basis of this algorithm. During the contest, the feebler empires collapse and their colonies seize by more powerful empires. Finally, the contest shapes a situation with only one empire in which the colonies and their imperialist have the same cost [32]. In this input selection problem, the last imperialist is the best combination of inputs suitable for proposed ANFIS model leading to the least targeting error.

Materials and Methods

Patients Group and Their Dataset

In this study, we used motion dataset of real 20 patients with tumors located at thorax region and move due to respiration. These patients were treated by CyberKnife Synchrony system (Accuray Inc., Sunnyvale, CA) at Georgetown University Medical Center (Washington, DC) [33-34]. In average, the dataset of each patient includes 100 samples (or data points); and 10 samples are gathered at pre-treatment step for correlation model construction and the rest of them are gathered during treatment for testing the accuracy of motion tracking and also model updating. Each sample is gathered instantly in the radiosurgery session, which includes the three-dimensional positions (x, y, z) of 1) three external surrogates as external dataset and 2) internal fiducial or implanted marker inside tumor volume representing tumor motion as internal dataset.

External dataset is collected by detecting some optical markers (placed on a specific vest at the thorax region) using optical (infrared) tracking system. On the other hand, internal dataset is revealed through a fiducial marker implanted inside or near the tumor volume and registered by a stereoscopic X-ray imaging system. After external-internal motion dataset gathering, a typical prediction model is constructed and then used for real-time tumor motion tracking radiotherapy [33-37].

ANFIS Correlation Model

The correlation model is configured using an external-internal training dataset gathered in the pre-treatment step and then the tumor position can be predicted by means of external data as model input. It should be noted that the model can be re-configured regularly using new arrival synchronized external-internal data points to check optimality of its performance during the treatment. The performance of common correlation models was considered as a comparative study in our recent works [21-24]. These models can be based on statistical and probabilistic methods, regression models, support vector machines [18-19], linear filters, adaptive filters, Kalman filters [21], artificial neural networks [21], fuzzy systems [21-24], a combination of neural networks and fuzzy systems [23], and ANFISs [24].

In this study, an ANFIS correlation model was chosen as the consistent correlation model due to its robustness proved in our previous study. The performance of this model is on the basis of fuzzy inference system in combination with an adaptive neural network [24].

We used fuzzy logic toolbox of MATLAB Version 2013b (The MathWorks Inc., Natick, MA) software to build the ANFIS correlation model. Our proposed ANFIS, the fuzzy if-then rules are based on Sugeno's type and the number of input membership function will be equal to the number of inputs [30] because the internal data belong to one fiducial marker with three dimensions; since ANFIS has three outputs, it has three output membership functions. Also, the number of chosen rules is equal to the number of inputs.

ICA as Input Selector

The external dataset is used as inputs for correlation model construction and performance. The number of inputs and the importance degree of each data point as input may affect the performance accuracy and computational time of correlation model. We therefore proposed implementing an input selection algorithm based on an optimization algorithm, called ICA, to choose the most effective and independent inputs for the correlation model. The selected inputs may lead to lower prediction errors and result in more concise and faster models.

ICA is an optimization algorithm stimulated by contest among imperialists in the real world. This evolutionary algorithm commences to work with a basic community of countries N_{pop}. The countries are $1\times N_{\text{var}}$ arrays and characterize as $Country=[p_1, p_2, p_3,..., p_{N_{\text{var}}}]$. In the countries, the changeable values that must be optimized are $[p_1, p_2, p_3,..., p_{N_{\text{var}}}]$ and the dimension of the optimization dilemma is N_{var}. By computing the cost function f for the changeable values, the cost of a country is obtained as follows:

$$cost = f(country) = f(p_1, p_2, p_3,..., p_{N_{\text{var}}}) \quad (1)$$

This cost shows how much the answer is close to the expected answer. In an input selection problem, this expected answer is a combination of inputs that results in a model with minimum error. The countries in the community (or individuals) have two dissimilar classes: Imperialists, the best countries in the community which have the least cost, and colonies, the rest of the individuals. Imperialists and colonies altogether make *empires*. All the colonies of basic community are divided among the just noticed imperialists based on their power, which is very similar to the fitness value in Genetic Algorithm. Before defining the power of an imperialist, the normalized cost of an imperialist is introduced by:

$$C_n = \max_i(c_i) - c_n \quad (2)$$

where c_n is the cost and C_n is the normalized cost of nth imperialist. Then, the normalized power of an imperialist is obtained by:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \quad (3)$$

In this equation, N_{imp} is the number of imperialists and P_n is the normalized power of the nth imperialist.

After calculating the normalized power, the initial number of colonies obtained by the nth imperialist is equal to:

$$N.C._n = round\{p_n \times N_{col}\} \quad (4)$$

where $N.C._n$ is the initial number of colonies obtained by the nth imperialist and N_{col} is the total number of colonies.

Then, after the dividing, the assimilation by moving colonies toward their pertinent imperialist begins. Figure 1 shows this movement; the colony progresses toward the imperialist x units.

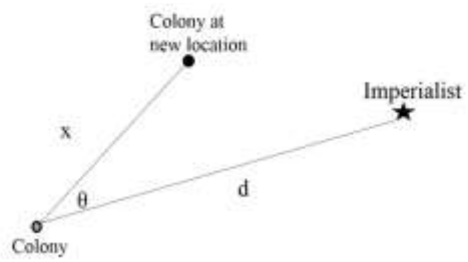

Figure 1. A direction with random deviation, the colony is approaching its imperialist.

In this figure, x and θ are random numbers with arbitrary distribution. When a colony is approaching its imperialist, the colony can discover a situation with lower cost than the imperialist cost. In such a situation, the colony and the imperialist exchange their position with each other and the colony becomes the new imperialist of the empire.

The power of the imperialist and a percentage of mean power of the colonies are the total power of an empire. This fact can be modeled by expressing the entire cost by:

$$T.C._n = \text{cost}(\text{imperialist}_n) + \xi \times \text{mean}[\text{cost}(\text{colonies of empire}_n)] \quad (5)$$

where $T.C._n$ is the total cost of the nth imperialist and ξ is a positive value smaller than 1 (usually equal to 0.1). The heart of this algorithm is the imperialistic contest among empires to seize more colonies. In this contest, if an empire cannot succeed to increase its power, it will be removed from the contest. This imperialistic contest leads to boost the power of more powerful empires and to decrease the power of powerless empires. The powerless empires become weaker and weaker, and finally, they collapse. The assimilation of colonies into their imperialists, contest among empires, and the collapse process will result in a circumstance in which there is only one empire with similar cost and position to its colonies [32].

The dataset has nine columns as inputs and the correlation model needs at least one input; so there are

$2^9 - 1$ or 511 different combinations of inputs. Only a few combinations of these 511 different combinations can minimize output Room Mean Square Error (RMSEs) of the ANFIS prediction model. In our optimization problem, ICA starts to work with an initial community of input combinations and it tries to find the best solution using a cost function, which is a very simple and fast ANFIS prediction model with similar characteristics to main prediction model. Finally, at the end of the algorithm, the only imperialist is the best solution or the best combination of inputs for the prediction model.

Before the ANFIS prediction model start to work, in the pre-treatment step, the ICA input selector begins to find the best combination of inputs by using its intelligent search mechanism and with the help of the cost function. The different combinations of inputs are tested by applying them to the simple and fast ANFIS model (cost function), and finally, ICA finds the best combination.

Study Plan

In order to assess the effect of ICA on the performance accuracy of correlation model and hence treatment quality, two strategies were taken into account: firstly, the model was constructed to work and get update without implementing ICA (as conventional tumor tracking used at clinical practice); secondly, the same strategy was done but by implementing ICA on input dataset of correlation model (as optimized tumor tracking proposed in this work). Then, targeting accuracy error of ANFIS model at two mentioned strategies were compared using RMSE at Excel software environment (Microsoft Corporation).

During the radiotherapy treatment course, the model output is checked intermittently using stereoscopic X-ray imaging system. This system takes an image from the real position of internal fiducial representing tumor position and this data is compared with model output to realize that the model is predicting tumor position properly. Otherwise, tumor tracking and treatment process is stepped till model re-configuration again. This checking process is done every 1 to 5 minutes and new paired data point can be used for model reconstruction for better predicting. The most important issue during updating is the time required for model re-building that must be in real time mode to prevent any possible interruption. It should be noted that computational time of model performance for tumor tracking is negligible. In this work, the computational time of reconstructing two ANFIS correlation models used at optimized tumor tracking versus conventional tumor tracking is compared relatively at the same condition by using an in-room computer system. This helps to realize the role of ICA on simplicity factor of correlation model that may improve the challenge of real-time mode at tumor motion tracking during treatment. Figure 2 shows the block diagram of ANFIS correlation model with ICA input selection algorithm.

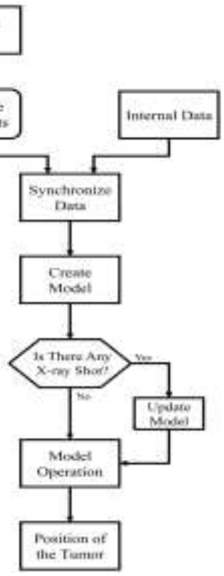

Figure 2. ANFIS correlation model with implementing ICA input selection algorithm

Results

At external surrogate's radiotherapy, each correlation model gives the 3D position of tumor location with an acceptable spatial uncertainty error. In this work, we used RMSE statistical tool to show this uncertainty error at two conventional and optimized tumor tracking strategies. RMSE is calculated according to the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \quad (6)$$

where N is the number of predicted samples, A_i is the ith actual output in the dataset, and P_i is the ith predicted output by the model. Our patient group included 10 patients with normal respiration and 10 patients with erratic and abnormal respiration.

Figures 3 and 4 show the RMSE of the proposed ANFIS model output over normal and erratic patients, respectively.

As both figures show, error fluctuation (error bar) is increasing while RMSE increases, that results the number of data points is low, during model construction. Inversely, while these data points is highest, the RMSE of tumor tracking is minimum (case 1, at normal patients). It is important to note that ICA optimization does not always lead to better results. For example, the optimization by ICA to choose the best inputs for the cases of P9 and P10 among the erratic group led to higher RMSEs compared with the conventional strategy. This may be due to the inability of ICA to choose the best combination of inputs among numerous combinations.

Figure 5 shows the average RMSEs over normal and erratic patients with and without implementing ICA. As seen in this figure, the optimized tumor tracking strategy over normal cases has better improvement regarding erratic cases.

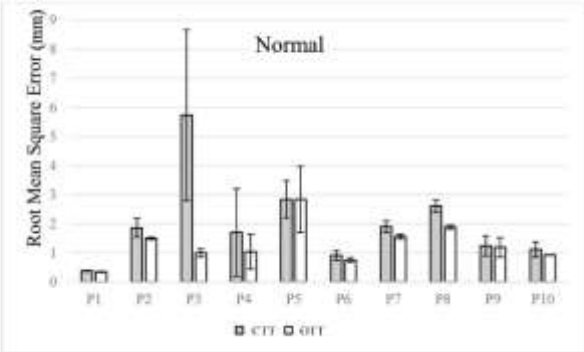

Figure 3. Calculated RMSE of ANFIS correlation model, Conventional Tumor Tracking (CTT) and Optimized Tumor Tracking (OTT) strategies for normal cases (P*i* is Patient number from *i*=1 to *i*=10 on X axis)

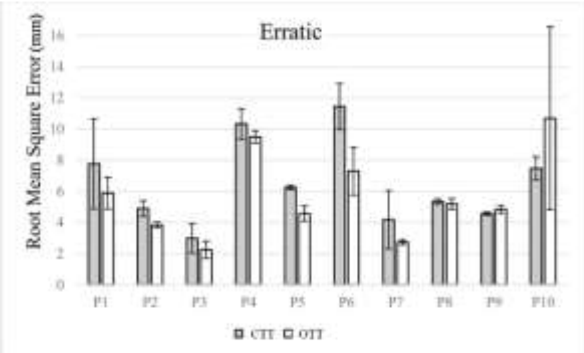

Figure 4. Calculated RMSE of ANFIS correlation model, Conventional Tumor Tracking (CTT) and Optimized Tumor Tracking (OTT) strategies for erratic cases ((P*i* is Patient number from *i*=1 to *i*=10 on X axis)

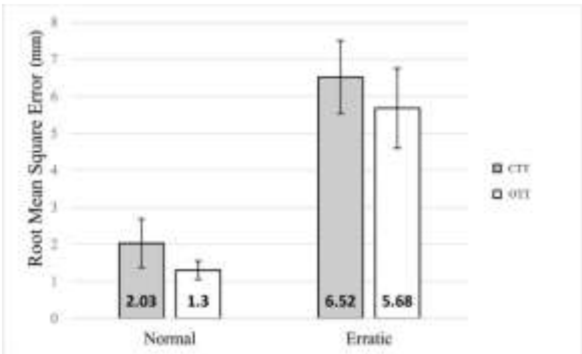

Figure 5. Average RMSE over all normal and erratic cases using Conventional Tumor Tracking (CTT) and Optimized Tumor Tracking (OTT) strategies

Moreover, the effect of ICA on the run-time factor has been considered. The results indicated a major run-time reduction after implementing ICA over normal and erratic cases with 45% and 43% against conventional strategy, respectively.

Discussion

In this work, an input selection method based on ICA was considered to improve targeting accuracy of typical correlation model utilized at RTRT with external surrogates. ICA was assumed to process the input motion dataset for an ANFIS as a proved consistent correlation model.

This algorithm makes better construction of ANFIS model at pre-treatment step, and therefore correlation between external surrogate's motion and tumor motion is achieved accordingly. ICA causes proper simplicity of ANFIS correlation model using selected data points with the most important degree among total input dataset that are intensive for the same cases. Model simplicity causes tumor tracking in real-time mode that is highly necessary in clinical application. In this study, 10 patients with normal breathing signals and 10 patients with erratic or abnormal breathing signals were used to provide required datasets for our proposed optimized strategy for tumor tracking. The final results showed that in 90% of total patients the proposed strategy could result in error reduction during tracking. In fact, ICA works by eliminating irrelevant unnecessary inputs and simplifies the correlation ANFIS model structure. Therefore, ICA is able to optimize the learning and reasoning parameters of ANFIS such as the number of membership functions and if-then rules.

However, at two cases in the erratic group, the performance of ICA was not essentially successful. This may be due to the inherent characteristics of optimization algorithms and input dataset (mainly from quantity point of view) that does not lead to a better answer. However, by implementation of ICA, the RMSE of correlation model reduced by 36% for the normal cases and 13% for the erratic cases compared to the conventional fashion. Another advantage of employing ICA is the run time of model construction during treatment. If there are unnecessary inputs, the model would become more complex and the number of model parameters and run-time would increase, that is an issue in RTRT. As the results showed, ICA could significantly improve run time reduction over all patients dataset.

Conclusion

The ICA data optimization algorithm could significantly improve the performance accuracy of our correlation model used at external surrogates' radiotherapy by eliminating unnecessary and noisy inputs and making the model simpler. Since a simpler model is more transparent and has fewer parameters, it may yield a lower run-time that is important at radiation treatment of dynamic tumors. Based on the results obtained in this study, the implementation of ICA optimization algorithm is promising for clinical application. Future studies may include the properties and behavior of other common available optimization algorithm on motion dataset processing at computer aided radiotherapy.

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References

1. Riboldi M, Sharp GC, Baroni G, Chen GT. Four-dimensional targeting error analysis in image-guided radiotherapy. Physics in medicine and biology. 2009; 54(19): 5995.
2. Liu HH, Balter P, Tutt T, Choi B, Zhang J, Wang C, et al. Assessing respiration-induced tumor motion and internal target volume using four-dimensional computed tomography for radiotherapy of lung cancer. International Journal of Radiation Oncology Biology Physics. 2007; 68(2): 531-40.
3. Onimaru R, Shirato H, Fujino M, Suzuki K, Yamazaki K, Nishimura M, et al. The effect of tumor location and respiratory function on tumor movement estimated by real-time tracking radiotherapy (RTRT) system. International Journal of Radiation Oncology Biology Physics. 2005;63(1): 164-9.
4. Seppenwoolde Y, Shirato H, Kitamura K, Shimizu S, Van Herk M, Lebesque JV, et al. Precise and real-time measurement of 3D tumor motion in lung due to breathing and heartbeat, measured during radiotherapy. International Journal of Radiation Oncology Biology Physics. 2002;53(4): 822-34.
5. Shirato H, Seppenwoolde Y, Kitamura K, Onimura R, Shimizu S. Intrafractional tumor motion: lung and liver. Seminars in radiation oncology. 2004;14(1):10-8.
6. Shirato H, Suzuki K, Sharp GC, Fujita K, Onimaru R, Fujino M,et al. Speed and amplitude of lung tumor motion precisely detected in four-dimensional setup and in real-time tumor-tracking radiotherapy. International Journal of Radiation Oncology Biology Physics, 2006;64(4): 1229-36.
7. Stevens CW, Munden RF, Forster KM, Kelly JF, Liao Z, Starkschall G, et al. Respiratory-driven lung tumor motion is independent of tumor size, tumor location, and pulmonary function. International Journal of Radiation Oncology Biology Physics. 2001;51(1): 62-8.
8. Wu J, Lei P, Shekhar R, Li H, Suntharalingam M, D'Souza WD. Do tumors in the lung deform during normal respiration? An image registration investigation. International Journal of Radiation Oncology Biology Physics. 2009;75(1): 268-75.
9. Hanley J, Debois MM, Mah D, Mageras GS, Raben A, Rosenzweig K, et al. Deep inspiration breath-hold technique for lung tumors: the potential value of target immobilization and reduced lung density in dose escalation. International Journal of Radiation Oncology Biology Physics. 1999;45(3): 603-11.
10. Kubo HD, Hill BC. Respiration gated radiotherapy treatment: a technical study. Physics in medicine and biology, 1996;41(1): 83.
11. Mah D, Hanley J, Rosenzweig KE, Yorke E, Braban L, Ling CC, et al. Technical aspects of the deep inspiration breath-hold technique in the treatment of thoracic cancer. International Journal of Radiation Oncology Biology Physics. 2000;48(4): 1175-85.
12. Minohara S, Kanai T, Endo M, Noda K, Kanazawa M. Respiratory gated irradiation system for heavy-ion radiotherapy. International Journal of Radiation Oncology Biology Physics, 2000;47(4): 1097-103.
13. Ohara K, Okumura T, Akisada M, Inada T, Mori T, Yokota H, et al. Irradiation synchronized with respiration gate. International Journal of Radiation Oncology Biology Physics, 1989;17(4): 853-7.
14. Shirato H, Shimizu S, Kunieda T, Kitamura K, Van Herk M, Kagei K, et al. Physical aspects of a real-time tumor-tracking system for gated radiotherapy. International Journal of Radiation Oncology Biology Physics. 2000;48(4): 1187-95.
15. Shirato H, Shimizu S, Shimizu T, Nishioka T, Miyasaka K. Real-time tumour-tracking radiotherapy. The Lancet. 1999. 353(9161): 1331-2.
16. Shimizu S, Shirato H, Ogura S, Akita-Dosaka H, Kitamura K, Nishioka T, et al. Detection of lung tumor movement in real-time tumor-tracking radiotherapy. International journal of radiation oncology, biology, physics. 2001;51(2): 304-10.
17. Shirato H, Harada T, Harabayashi T, Hida K, Endo H, Kitamura K, et al. Feasibility of insertion/implantation of 2.0-mm-diameter gold internal fiducial markers for precise setup and real-time tumor tracking in radiotherapy. International Journal of Radiation Oncology Biology Physics. 2003;56(1): 240-7.
18. Alnowam MR, Lewis E, Wells K, Guy M. Respiratory motion modelling and prediction using probability density estimation. in Nuclear Science Symposium Conference Record (NSS/MIC). 2010;2465-9. IEEE.
19. Riaz N, Shanker P, Wiersma R, Gudmundsson O, Mao W, Widrow B, et al. Predicting respiratory tumor motion with multi-dimensional adaptive filters and support vector regression. Physics in medicine and biology. 2009;54(19): 5735.
20. Keall PJ, Mageras GS, Balter JM, Emery RS, Forster KM, Jiang SB, et al. The management of respiratory motion in radiation oncology report of AAPM Task Group 76. Medical physics. 2006;33(10): 3874-900.
21. Torshabi AE, Pella A, Riboldi M, Baroni G. Targeting accuracy in real-time tumor tracking via external surrogates: a comparative study. Technol Cancer Res Treat. 2010;9(6): 551-62.
22. Torshabi AE, Riboldi M, Fooladi AA, Mosalla SM, Baroni G. An adaptive fuzzy prediction model for real time tumor tracking in radiotherapy via external surrogates. Journal of Applied Clinical Medical Physics. 2013 ;14(1):102-14.
23. Torshabi AE. Investigation of the Robustness of Adaptive Neuro-Fuzzy Inference System for Tracking of Moving Tumors in External Radiotherapy, Australian Physical and Engineeing Sciences in Medicine. 2014;37(4):771-8.
24. Ghorbanzadeh L, Torshabi AE, Nabipour JS, Arbatan MA. Development of a Synthetic Adaptive Neuro-fuzzy Prediction Model for Tumor Motion Tracking in External Radiotherapy by Evaluating Various Data Clustering Algorithms. Technology in Cancer Research and Treatment. 2016;15(2):334-7.
25. Esmaili Torshabi A, Ghorbanzadeh L. A study on stereoscopic X-ray imaging data set on the accuracy of real time tumor tracking in external beam radiotherapy. Technology in Cancer Research and Treatment. 2017;16(2):167–77.
26. Nankali S, Torshabi AE, Miandoab PS. A feasibility study on ribs as anatomical landmarks for motion

tracking of lung and liver tumors at external beam radiotherapy. Technology in Cancer Research and Treatment. 2017;16(1): 99‑111.

27. Miandoab PS, Torshabi AE, Nankali S. Investigation of the optimum location of external markers for patient setup accuracy enhancement at external beam radiotherapy. Journal of applied clinical medical physics. 2016; 17(6): 32‑43.
28. Samadi Miandoab P, Esmaili Torshabi A, Parandeh S. Calculation of inter-and intra-fraction motion errors at external radiotherapy using a markerless strategy based on image registration combined with correlation model. Iranian Journal of medical physics. 2019; 16(3): 224-31.
29. Jang JS. ANFIS: adaptive-network-based fuzzy inference system, Systems, Man and Cybernetics, IEEE Transactions on. (1993);23(3):665-85.
30. Takagi T, Sugeno M. Fuzzy identification of systems and its applications to modeling and control, Systems, IEEE Transactions on Man and Cybernetics. 1985; 15:116-32.
31. Jang, JS. Input selection for ANFIS learning, Proceedings of the Fifth IEEE International Conference on Fuzzy Systems. 1996;1493-9.
32. Atashpaz-Gargari E, Lucas C. Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. in Evolutionary Computation, 2007. CEC 2007. IEEE Congress on. 2007. IEEE.
33. Schweikard A, Glosser G, Bodduluri M, Murphy MJ, Adler JR. Robotic motion compensation for respiratory movement during radiosurgery. Computed-Aided Surgury. 2000;5(4): 263‑77.
34. Kilby W, Dooley JR, Kuduvalli G, Sayeh S, Maurer Jr CR. The CyberKnife Robotic Radiosurgery System in 2010. Technology in Cancer Research and Treatment. 2010;9(5):433-52.
35. Seppenwoolde Y, Berbeco RI, Nishioka S, Shirato H, Heijmen B. Accuracy of tumor motion compensation algorithm from a robotic respiratory tracking system: a simulation study. Medical Physics. 2007;34(7):2774-84.
36. Hoogeman M, Prévost JB, Nuyttens J, Pöll J, Levendag P, Heijmen B. Clinical accuracy of the respiratory tumor tracking system of the cyberknife: assessment by analysis of log files. International Journal of Radiation Oncology Biology Physics. 2009;74(1):297-303.
37. Pepin EW, Wu H, Zhang Y, Lord B. Correlation and prediction uncertainties in the cyberknife synchrony respiratory tracking system. Medical Physics. 2011;38(7):4036-44.