Proceedings of the International MultiConference of Engineers and Computer Scientists 2015 Vol II,
IMECS 2015, March 18 - 20, 2015, Hong Kong

Indirect Tracking of Functional Target for Respiration Compensation in Radiotherapy

Rūta Užupytė, Ka Lok Man, Tomas Krilavičius, Indrė Žliobaitė, and Henrikas Simonavičius

***Abstract*—The main goal of radiotherapy is to destroy the tumor while minimizing harm to nearby healthy tissue. In order to achieve an effective and accurate treatment, motion of the target, caused by respiration, should be taken into account when positioning the beam. This paper presents a work-in-progress on computational techniques for identifying tumor position from an external marker during treatment session.**

***Index Terms*—respiratory radiotherapy, respiratory tumor motion, regression.**

I. Introduction

RADIOTHERAPY aims at focused emission of radiation dose to the target volume of tissue, while minimizing exposure to radiation for the surrounding healthy tissue. A number of accurate approaches to treatment already exists [1], [2]; however, motion compensation during treatment remains a challenging issue. Several alternative techniques are analyzed in [3], overview of models for predicting movement of tumor is given in [4].

In this paper we present a work–in–progress, which aims at proposing a technique for predicting a tumor position from the position of an external marker during a treatment session. Our previous investigation [5] shows that a standard linear regression can predict the motion of an internal target with a reasonable accuracy, but a major limiting factor for the performance is presence of autocorrelation of the observations. In this study we present an approach for dealing with the problem of autocorrelation using models with first–order autoregressive errors. Our experimental results demonstrate that the proposed methodology solves the problem of autocorrelation, but also decreases models forecasting performance.

The paper is organized as follows. In section II problem formulation, and computational methods are presented. Section III discusses data collection, and provides an overview of our previous approaches. Section IV discusses experimental results. Section V presents concluding remarks, and discusses future research.

II. Methodology

A. Problem Formulation

Suppose, we have two time series $M = o_1, o_2, \ldots, o_n$ and $T = p_1, p_2, \ldots, p_n$ consisting of n observations, where $o_i = (x_i^m, y_i^m)$ is a two–dimensional vector indicating the position of an external marker at time i while $p_i = (x_i^t, y_i^t)$ is a two–dimensional vector indicating the position of the target at time i. Our goal is to find an expression of functional relationship $T = \mathrm{F}(M)$ between the signals, separately for each component:

$$x^t = \mathrm{F}_1(x^m), \tag{1}$$
$$y^t = \mathrm{F}_2(y^m), \tag{2}$$

where the relations F_1 and F_2 are assumed to have the same functional form, but different values of the parameters.

B. Evaluation of performance

Suppose, we have a testing dataset consisting of n observations, where $p_i = (x_i^t, y_i^t)$ is the true position of the tumor at time i, and $\hat{p}_i = (\hat{x}_i^t, \hat{y}_i^t)$ is our prediction for the same time i. To evaluate the accuracy of prediction we use two different measures:

1) the mean absolute error, i.e. the average distance from the predicted position to the true position of the tumor:
$$MAE = \frac{\sum_{i=1}^{n} \sqrt{(\hat{x}_i^t - x_i^t)^2 + (\hat{y}_i^t - y_i^t)^2}}{n}. \tag{3}$$
2) the root mean square error, i.e. the sample standard deviation of the differences between predicted and observed tumor position:
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{x}_i^t - x_i^t)^2 + (\hat{y}_i^t - y_i^t)^2}{n}}. \tag{4}$$

C. Linear regression

A linear regression assumes that two variables are systematically linked by a linear relationship. The general form of a linear regression is:

$$y = \beta_0 + \beta_1 x + \varepsilon, \tag{5}$$

where x is the input variable, y is the response (predicted) variable, (β_0, β_1) are model parameters, and ε is a random error. Ordinary least squares method [6] is a typical approach for estimating the unknown model parameters (β_0, β_1), given a set of observations (x, y).

One of the key assumptions behind the linear regression model is that the errors ε are independent from each other, i.e. $\mathrm{E}(\varepsilon_t \varepsilon_s) = 0$, when $t \neq s$ and when $t = s$, $\mathrm{E}(\varepsilon_t)^2 = \sigma^2$, where $\mathrm{E}(x)$ denotes the mean of x, and σ^2 denotes the variance of ε_t. If $\mathrm{E}(\varepsilon_t \varepsilon_s) \neq 0$, then the assumption is violated, and the regression model has a problem of autocorrelation. Mathematically first–order autocorrelation means that the model errors satisfy a recursive relationship [7]:

$$\varepsilon_t = \rho \varepsilon_{t-1} + u_t, \tag{6}$$

Manuscript received January 08, 2015; revised February 10, 2015. Research was partially financed by REPOZ PILOT (VP2-1.3-ŁM-02-K-03-031) and Employment of High Qualification Specialist in Baltic Institute of Advanced Technology to Perform Research (VP1-3.2-MM-01-K-02-002)

T. Krilavičius, R. Užupytė are with the Baltic Institute of Advanced Technology and Vytautas Magnus University, Lithuania , e-mail: t.krilavicius, ruta.uzupyte@bpti.lt

I. Žliobaitė is with Aalto University, Finland, e-mail:zliobaite@gmail.com

Ka Lok Man is with Xi'an Jiaotong-Liverpool University, China, e-mail:ka.man@xjtlu.edu.cn

H. Simonavičius is with UAB Rubedo Systems, Lithuania

TABLE I
PREDICTION ERROR FOR SELECTED MODELS

Model	Standard linear regression						Linear regression with AR(1) errors					
	MAE, mm	RMSE, mm	p–value		R^2		MAE, mm	RMSE, mm	p–value		R^2	
			x	y	x	y			x	y	x	y
P4∼P0	0.55	0.69	0	0	0.96	0.89	0.56	0.7	0.82	0.96	**0.97**	**0.93**
P4∼P1	0.79	0.94	0	0	0.93	0.74	0.79	0.93	0.35	0.5	0.94	0.76
P4∼P2	0.89	1.04	0	0	0.87	0.81	0.84	0.97	0.36	0.9	0.91	0.83
P5∼P0	0.51	0.64	0	0	0.53	0.81	**0.53**	**0.68**	0.09	0.85	0.69	0.9
P5∼P1	0.61	0.73	0	0	0.55	0.7	0.61	0.73	0.10	0.85	0.68	0.74
P5∼P2	0.61	0.73	0	0.03	0.72	0.86	0.6	0.71	0.72	0.91	0.74	0.86
P7∼P0	0.62	0.77	0	0	0.82	0.88	0.62	0.77	0.30	0.7	0.86	0.9
P7∼P1	0.87	1.05	0	0	0.83	0.72	0.87	1.04	0.77	0.36	0.85	0.74
P7∼P2	0.95	1.12	0	0	0.66	0.8	0.91	1.05	0.34	0.82	0.77	0.82
P8∼P0	0.85	1.03	0.13	0	0.94	0.85	0.85	1.03	0.13	0.74	0.94	0.89
P8∼P1	1.04	1.26	0.03	0	0.91	0.68	1.04	1.26	0.91	0.37	0.91	0.7
P8∼P2	1.1	1.32	0	0	0.85	0.77	1.04	1.24	0.47	0.62	0.86	0.7

where $\{u_t, t = 1, 2, ...n\}$ is a sequence of independent random variables, which are normally distributed with zero mean and a constant variance, and ρ is the autoregressive coefficient ($|\rho| < 1$). When $\rho = 0$, errors ε_t are uncorrelated. The most typical case is the first–order autoregressive error. For determining whether the errors are following the first–order autoregressive process, we use the Durbin–Watson test [8].

If autocorrelation is found, we modify the model by including the estimated first–order autoregressive coefficient of the error term:

$$y_i = \beta_0 + \beta_1 x_i + e_i, \tag{7}$$

$$e_i = \rho e_{i-1} + \varepsilon_i, \tag{8}$$

where e_i are regression model residuals, ε random error and ρ is autoregressive coefficient which can be computed using residuals of initial model (equation (5)):

$$\hat{\rho} = \frac{\sum_{i=2}^{n} e_i e_{i-1}}{\sum_{i=2}^{n} e_{i-1}^2}. \tag{9}$$

III. Data collection

Respiratory motion data was collected with MRT Achieva XR (Philips Medical Systems) (with a 16–channel SENSE XR Torso coil). We collected data of 8 different persons using three external markers placed at different positions. Records were produced in DICOM[1]. Time series from the records were extracted using in–house tools, where several (6—10) points–of–interest (POI) were tracked instead of tumors. The duration of the records varied from 300 to 500 frames, i.e. 150—400 sec. Overall, 87 signal–pairs were obtained. However, some signals (6) were deemed useless, because either target or marker did not move. All signals were defined by two components: one part of the signals had lateral and anterior-posterior directions (superior inferior direction was ignored), and another part had anterior–posterior and superior inferior directions (lateral direction was ignored).

Our previous research [5] showed that the majority of the signals were linked by strong or medium relationships: data correlation varied from 0.001 to 0.991 with the mean equal to 0.492. The lowest degree of correlation were obtained using markers with failed detection. Correlation analysis showed that there is a linear relationship between two signals, based on these results a linear model was chosen.

[1]Digital Imaging and Communications in Medicine (DICOM) is *de facto* standard for handling, storing, printing, and transmitting information in medical imaging.

TABLE II
PREDICTION ERROR OVER ALL MODELS

	Standard lin. regression		Lin. regression with AR(1)	
	MAE,mm	RMSE, mm	MAE,mm	RMSE, mm
Average	1.069	1.245	1.074	1.252
Min	0.26	0.29	0.26	0.29
Max	3.44	4.01	3.76	4.28

Data transformation was applied before further analysis, i.e. each time series was normalized such that the minimum value is zero, and the maximum is equal to $\max(P_i) - \min(P_i)$, as follows

$$x'_{ij} = x_{ij} - \min(x_{i1}, x_{i2}, \ldots, x_{in}), \tag{10}$$

$$y'_{ij} = y_{ij} - \min(y_{i1}, y_{i2}, \ldots, y_{in}), \tag{11}$$

where $P_i = \{p_{i1}, p_{i2}, \ldots, p_{in}\}$ is a time series consisting of n observations and $p_{ij} = \{x_{ij}, y_{ij}\}$.

IV. Experimental analysis

We randomly allocated 50% of the data to the training set, and 50% to the test set. All possible pairs between external markers and internal points–of–interest were analyzed. Each coordinate of internal signal was predicted separately based on the corresponding coordinate of the external marker. Part of the results are provided in Table I.

The table shows that almost all the standard linear regression models suffer from the problem of autocorrelation, since in most cases p–values of the Durbin–Watson test are lower than 0.05. In order to solve this problem we used a modified version of the regression model that takes into account the first–order autoregressive errors. The results are reported in the same Table I.

Comparing the results obtained by the linear regression model with the first–order autoregressive errors we can see that all p–values of Durbin–Watson test are greater than 0.05, which suggests that the problem of autocorrelation was solved. Moreover, the proposed models have larger values for the coefficient of determination (R^2), i.e. models with first–order autoregressive errors fit the data better.

In Table II we analyze the testing accuracies (MAE and RMSE) over all the models. We can see that average values slightly increased due to taking into account the first-order dependencies. More substantial changes are observed in maximum values of accuracy measures. Since the main goal is to find model with the best forecasting performance it can be concluded that simple linear regression model are more suitable for functional target tracking in comparison with simple linear model with AR(1) errors.

Results in Table I suggest that the prediction accuracy relates to the position of an external marker. More accurate predictions are obtained using external markers placed in position P0 –area of the abdomen. Also we can see that models P4∼P0 show the best fit R^2 (see fig. 1, fig 2), while the minimum testing error is observed for relation P5∼P0 (see fig. 3, fig 4).

This difference can be due to the nature of evaluation criteria: MAE is an average distance while $RMSE$ is the standard deviation from the predicted position to the true position of the internal point, i.e. the prediction accuracy depends on the range of the signal motion. However, relatively high values of the coefficient of determination show that the predictive power of the models is quite good.

V. Conclusion

We have demonstrated that the problem of autocorrelation can be solved using a standard linear regression model with first-order of autoregressive errors. Despite the fact that this methodology improves the values of the coefficient of determination, the slight decrease in testing accuracy was observed. Furthermore, results show that more accurate predictions are obtained using external markers placed in the area of the abdomen. In the future we are going to use other quality measures because in this research presented loss functions (MAE, $RMSE$) depend on the range of the signal motion. Moreover, in the future we are planning to perform experiments with more complex methods such as multiple regression and nonlinear models. Furthermore, we are planning to analyze respiratory motion prediction and design cases of an overall system radiation therapy system with respiratory motion compensation.

Acknowledgment

The authors would like to thank G. Čaplinskas for extracting trajectories from MRI images.

References

[1] G. D. R. and C. J. Y, “Adaptive radiation for lung cancer,” *Journal of Oncology*, vol. 2011, 2010.

[2] B. S. A. and N. C. M., “Recent advances in radiotherapy,” *BMC Medicine*, vol. 8, no. 1, 2010.

[3] M. G. S. Keall P.J and et. al., “The management of respiratory motion in radiation oncology report of aapm task group 76,” *Medical Physics*, vol. 33, no. 10, pp. 3874–3900, 2006.

[4] M. M. J., “Tracking moving organs in real time,” *Seminars in Radiation Oncology*, vol. 14, no. 1, pp. 91–100, 2004.

[5] v. I. Krilavičius T., Užupytė R. and S. H., “Correlation of external markers and functional targets for respiration compensation in radiotherapy,” in *Proc. of Medical Physics in the Baltic States, Kaunas, Lithuania, Oct, 2013*, pp. 42–45.

[6] J. F. T. Hastie, R. Tibshirani, *The elements of statistical learning : data mining, inference, and prediction*, 2nd ed., ser. Springer series in statistics. New York: Springer, 2009.

[7] H. Barreto and F. Howland, *Introductory Econometrics: Using Monte Carlo Simulation with Microsoft Excel*. Cambridge, 2006.

[8] D. Conniffe, “Tightening durbin-watson bounds,” *The Economic and Social Review*, vol. 28, pp. 351–356, 1997.

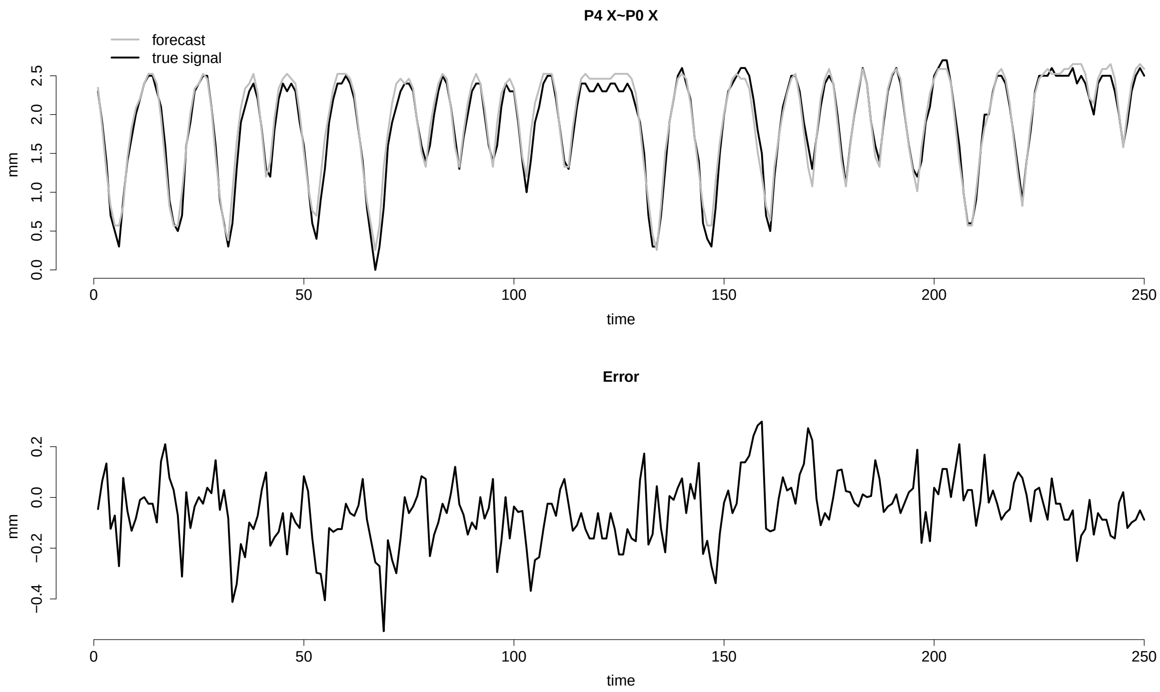

Fig. 1. Forecast and error term of x from relation P4∼P0

ISBN: 978-988-19253-9-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

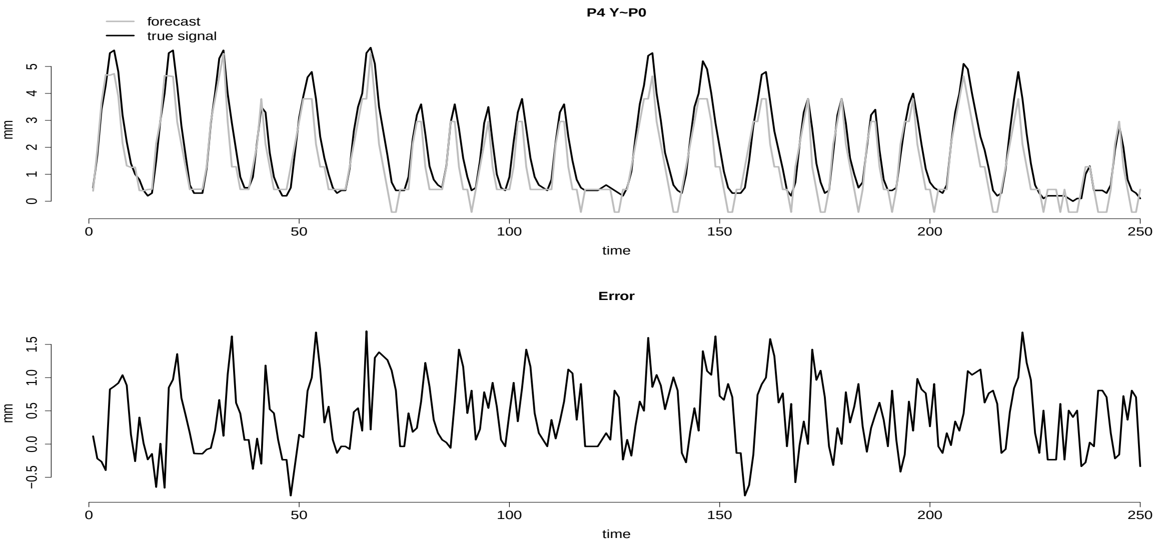

Fig. 2. Forecast and error term of y from relation P4∼P0

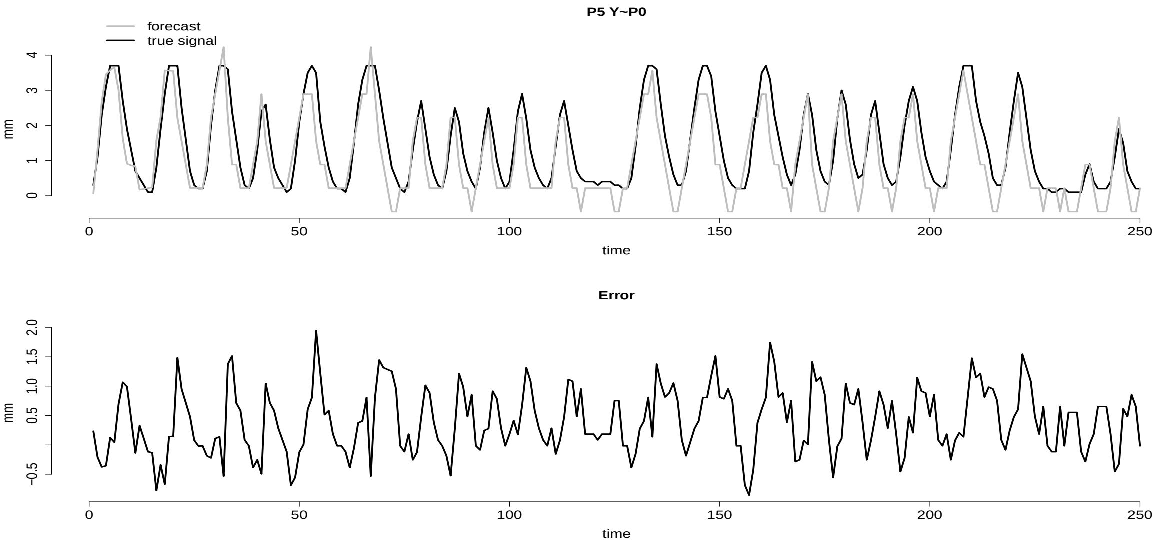

Fig. 3. Forecast and error term of x from relation P5∼P0

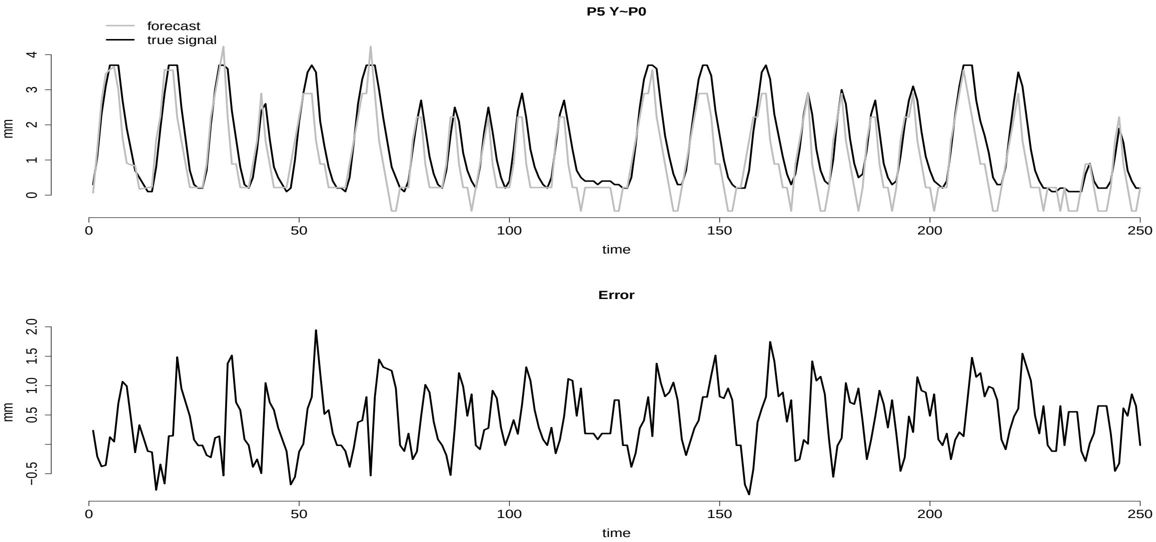

Fig. 4. Forecast and error term of y from relation P5∼P0

ISBN: 978-988-19253-9-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)