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A prospective tracking algorithm for motion compensation radiotherapy

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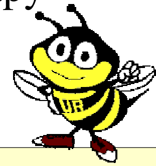

I. Introduction

Motion compensated [1-3] or respiration gated [4,5] radiotherapy systems are currently available. Signals representing moving targets can be obtained from either real-time x-ray images of implanted markers near the target or external respiration sensors. However, a time lag exists between the motion signal acquisition and action execution. A previous study has shown that typical respiratory velocity of 2-4 mm/sec results in a systematic position lag between 1 and 2 mm, and a time lag of 0.3 seconds [3]. This systematic lag could be compensated by predicting motions because the regularity of breathing signals would allow for such a prediction to a limited extent in the future. The purpose of this study is to test the feasibility of the prospective tracking method to predict the future trajectory of the target based on the previous motion signals in motion-compensation or gated radiotherapy.

II. Methods

A. *Autoregressive (AR) Model*

The autoregressive (AR) model [6,7] is one of the linear prediction formulas that attempt to predict an output y_n of a system based on the previous inputs (x_n, x_{n-1}, x_{n-2}...). It is also known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter, and is sometimes known as a maximum entropy model in physics applications. The definition used here is as follows

$$y_n=\sum_{i=1}^{n} a_i x_{n-i} + \ _n \qquad (1)$$

where a_i are the autoregression coefficients, x_i is the series under investigation, and *n* is the order (length) of the filter which is generally less than the length of the series. The noise term or residue, epsilon in the above, is almost always assumed to be Gaussian white noise.

The current term of the series can be estimated by a linear weighted sum of previous terms in the series. The weights are the autoregression coefficients. The problem in AR analysis is to derive the "best" values for a_i given a series x_i. The majority of methods assume the series x_i is linear and stationary. By convention the series x_i is assumed to be zero mean, if not this is simply another term a_0 in front of the summation in the equation above.

A number of techniques exist for computing AR coefficients. The main two categories are least squares and Burg method. Within each of these there are a few variants, the most common least squares method is based upon the Yule-Walker equations. MatLab has a wide range of supported methods, including the Burg's, covariance, and modified covariance methods. We tested each of these three methods, and the dependence of the predicted errors on the model order and the input data length.

B. *Electromagnetic position measurement system*

For the purpose of position measurement in this study, an electromagnetic (EM) position and orientation measurement system (miniBIRD™, Ascension Technology, Inc., Burlington, Vermont) was used. An EM sensor was attached to the subject's chest and real-time position respiratory signals were acquired. An EM transmitter was mounted on a wood stand and settled about 30~40cm distance to the sensor. Both the sensor and the transmitter were connected with an electronics unit, which was connected to the computer through RS232 serial port. An in-house C++ application program was developed to acquire the real-time respiratory signal, calculate the model, and predict the next positions. The respiratory signals were obtained at a frequency of 3 Hz. The AR model was updated every 10 seconds, and signals of 10 seconds (about 30 points) were used to compute the AR model coefficients. The model order was dependent on the method: for Burg's method, it was set as half of the data array length. The same model was used for 10 seconds while the input data array was updated with the actual signals. The predicted positions were computed. The position error of the predicted signal was computed as the average value of the absolute differences of each point pair between the original signal and the predicted signal:

$$E_{predicted}=\frac{1}{M}\sum_{i=1}^{M}|y_i - x_i| \qquad (2)$$

where *M* is the total number of predicted points. The position error allowing for time lag was computed through shifting the respiration signal by one time unit (~0.33 seconds), and then computing the average value of the absolute differences between each point pairs of the original signal and the shifted signal:

$$E_{shifted}=\frac{1}{M}\sum_{i=1}^{M}|x_i - x_{i-1}| \qquad (3)$$

III. Results

A. *Original and Predicted Respiratory Signals*

A free-breathing respiration signal of a healthy volunteer was acquired by attaching the EM sensor to his chest. About 1 min. of free breathing was recorded. The entire series contains about 180 data points, as shown in Fig. 1. The averaged one time unit shifted error of this signal was 0.8 mm, as computed by Eq. (3). Figure 2 showed the predicted signal of the series using Burg's method. There were 30 input data points and the order was 15. The predicted error was 0.35 mm, as computed by Eq. (2)

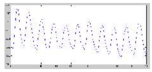

Fig. 1.

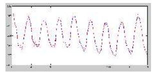

Fig. 2.

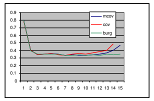

Fig. 3.

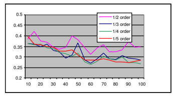

Fig. 4.

B. *Selection of the model order*

There is no straightforward way to determine the correct model order. Generally, as one increases the order of the model the average error decreases quickly up to some order and then more slowly. An order just after the point at which the RMS error flattens out is usually appropriate. Selection of the order used to compute the AR model coefficients was experimentally tested in this study, and shown in Fig. 3. The minimum predicted errors were 0.33 mm for the Burg's method and the modified covariance method, when the orders were 10, and 0.34 mm for the covariance method when the order was 7.

C. *Selection of the input data length*

The relationship between the predicted errors and the number of points used as input signal was tested, by changing the input data length from 10 to 100 with the step size of 5. Four different orders were used, as defined by the fraction of the input data length, 1/2, 1/3, 1/4, and 1/5, respectively. The results were shown in Fig. 4. The minimum predicted error was 0.25 mm when 60 data points were used and the order was 17. This test was performed using the Burg's method. The other methods showed similar results. The minimum errors were 0.26 and 0.27 mm for the covariance and modified covariance method, respectively.

Fig. 1. The original respiratory signal (only one dimensional position was shown here and used in the study). The horizontal axis is the time unit (~0.33s per point), and the vertical axis is the position in units of mm.

Fig. 2. The predicted signal (in red) compared with the original signal (in blue). AR model coefficient computed using Burg's method.

Fig. 3. Relationship between the predicted errors and the orders used to compute the AR model coefficients (30 input points).

Fig. 4. Relationship between the predicted errors and the input data length used to compute the AR model coefficients (4 different orders).

IV. Conclusions and Discussions

In a typical test case, the minimum predicted error of free-breathing respiration signals of a healthy volunteer was 0.25 mm, while the shifted error allowing for time lag was 0.8 mm. The predicted error is dependent on the model order and the input data length. For this typical case, the minimum predicted error was realized when the data input length was 60 points (corresponding to 20 seconds or 3 full respiratory cycles of free-breathing of the subject), and the order was ¼ of the input data length.

In respiration-gated radiation therapy, high-energy photon beam of fixed or varying aperture and/or intensity is switched on under computer control during a desired portion of the respiratory cycle, in which movement of the target volume (tumor) is minimized. The prospective tracking model should therefore predict the locations of the peaks and valleys (end-inspiration and end-expiration) as well as the full-width at half-maximum of the real-time signals accurately. Additional tests will be performed in the near future, including (a) test signals from different positions on the torso (e.g. different parts of the chest and abdomen); (b) introduce "shock" to the respiration signal (sudden change in breathing pattern); and (c) introduce "trend" using an auto-regressive moving average model (e.g., fast then relaxing, or slow-fast-slow). These refinements to the basic model may better account for realistic clinical situations in radiotherapy with the patient under treatment. The validity and efficacy of the refined prospective tracking model will be investigated in a future clinical study in which respiratory signals obtained from patients under radiotherapy treatments are acquired and used to assess its accuracy.

V. References

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