Location Prediction of Moving Target

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AAPM 2009

Outline of Topics

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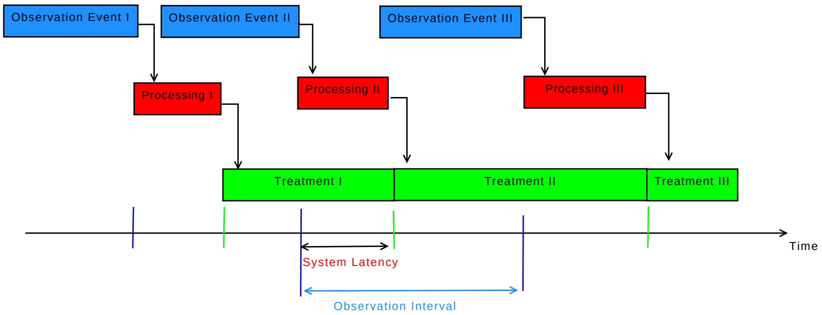
Disclaimer: unless indicated otherwise, the views in this talk represent personal opinion, not an official statement of AAPM or Stanford University.

Outline

Motivation

- Adaptive therapy with online motion compensation
  At each time instant, requires
  Target localization $\Rightarrow$ Treatment adaptation.
- System latency is ubiquitous: necessitates prediction (estimation with delayed observations).
  $\underline{\text{[Motion Monitoring + Prediction]}}$ $\Rightarrow$ Treatment adaptation
- From a filtering perspective, prediction (extrapolation) is a viable option for handling asynchronous multiple observation streams in hybrid systems.

Problem description



Goal: given an observed sample path $\{s_i\}_{i=1}^{K}$, to *causally* estimate the underlying state s_{K+L} at a future time (times).

Talk will focus on intra-fraction respiratory motion, idea generalizes.

Key factors

- observation (sample path) mode - usually discrete $\{s_i\}$.
  - sampling pattern (uniform v.s. non-, rate)
  - uncertainty
  - missing samples/outliers? detectable?
- prediction requirement:
  - setup: prediction horizon pattern (fixed length, varying, continuous)
  - accuracy requirement
- state definition:
  - instantaneous target dynamics (location, velocity, etc., with possibly categorical classification).
  - instantaneous anatomical configuration.

Two perspectives

- **Deterministic perspective**
  Consider the *underlying state* as *deterministic unknown* $\Rightarrow$ estimate its value , explicitly seek $\hat{s}$.
  - sample path modeling: most intuitive.
  - deterministic regression: estimates a *deterministic* input/output map from the observed portion of sample path.

Two perspectives

- **Deterministic perspective**
  Consider the *underlying state* as *deterministic unknown* $\Rightarrow$ estimate its value , explicitly seek $\hat{s}$.
  - sample path modeling: most intuitive.
  - deterministic regression: estimates a *deterministic* input/output map from the observed portion of sample path.
- **Stochastic perspective**
  Consider the *underlying state* as *stochastic unknown* $\Rightarrow$ estimate its distribution.
  - random process modeling: most stochastic filtering schemes
  - ...

Categorization of Prediction Schemes

	Sample Path Est.	Regression
Deterministic		
Stochastic		

Categorization of Prediction Schemes

	Sample Path Est.	**Regression**
Deterministic	Cosine, Fourier, Wavelet, Piecewise Linear, ARMA	ANN, SVM, LOESS
Stochastic	Stochastic filter, *e.g.*, KF, PF	...

Outline

Sample path estimation via motion modeling

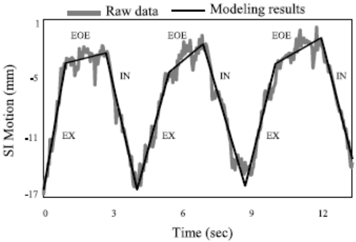
- Sample path modeling: generally seeks a complete temporal-spatial description of the underlying evolving state by modeling the feasible sample path.
  Any method that reminds you of a sketching procedure...

- Major playground: representation

e.g. modified cosine model[Lujan 94], local linear model[Wu 04], wavelet + AR[Ernst 07], real-time profiling[Ruan 09]

Local linear representation

- A normal breathing cycle is decomposed into three stages: inhale(IN), exhale(EX), and end of exhale (EOE).
- Periodic progression in/out of each linear segment is modeled with a discrete set of rules, local parameters estimated.
- Potential local continuous prediction capability.



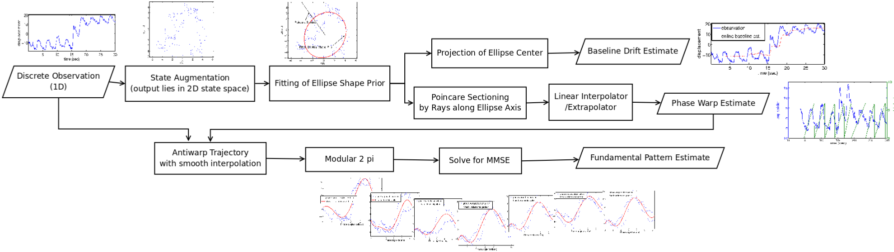
Profiling representation

- The observations are considered as noisy discrete samples from a periodic shape subject to phase warping and baseline drift.

$$s_i = [f_T(\phi(t)) + b(t) + w(t)]|_{t=t_i}.$$

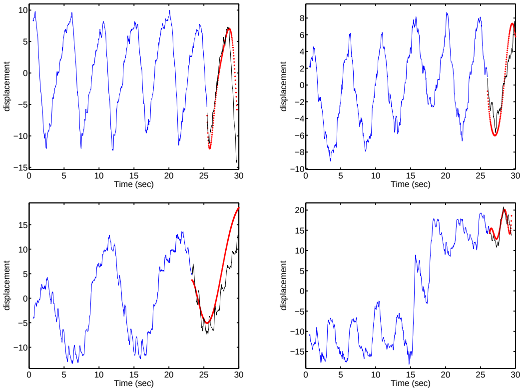
- The online profiling system estimates the instantaneous shape f_T, phase warping ϕ (thus frequency variation) and baseline drift b in real-time.

Profiling schematic



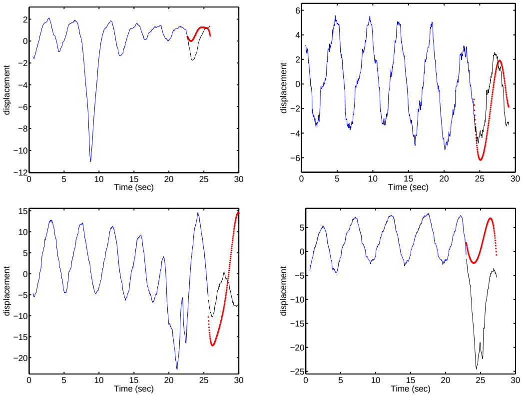
- robust to nonuniform samples, high observation noise, outliers.
- provides functional descriptor with natural continuous horizon prediction.

Profiling applied to prediction (cont.)



available observation, unknown observation, prediction with profiling extrapolation.

Profiling applied to prediction



available observation, unknown observation, prediction with profiling extrapolation.

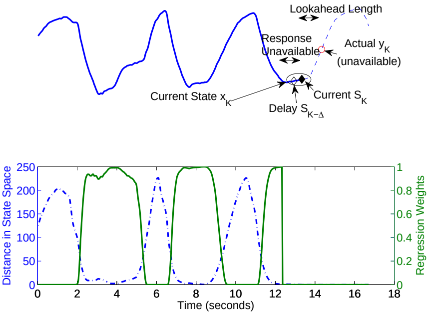
Deterministic regression for state prediction

- Location prediction with deterministic regression: assumes a consistent relationship between a recent observed temporal segment and the state after a fixed latency. The goal is to estimate such a consistent map.
  Any method that deterministically "learns" from input-output pairs.

- Major playground: functional approximation and estimation.

e.g. LOESS [Ruan 06], ANN[Murphy 06], SVM[Ernst 08], ANFIS [Kakar, 05]

Generating input-output pairs for regression



- input $\mathbf{x}_i = [s_{i-(p-1)\Delta}, \ldots, s_{i-\Delta}, s_i]$, concatenation of p delayed samples
- output $\mathbf{y}_i = s_{i+L}$, discrete lag L corresponds to prediction length
- With most current sample s_K, training set $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i<K-L}$. Testing input: $\mathbf{x}_K$, want $\hat{\mathbf{y}}_K$.
- Goal: learn map $g : \Re^p \rightarrow \Re$, $\mathbf{y} \approx g(\mathbf{x})$ from training set, especially around input $\mathbf{x}_K$.

Functional estimation

Parametric: LOESS

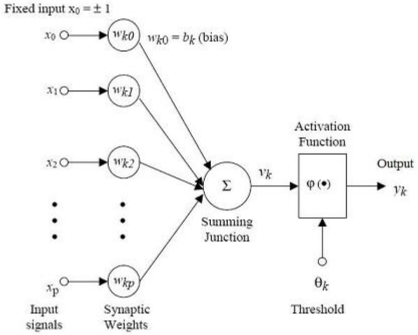
- assume $g(\mathbf{x}) = \sum_{q=1}^{Q} \beta_q z_q(\mathbf{x})$ with tensor basis z_q.
- determine local inference weight

$$w_i = \kappa(h_K^{-1} \|\mathbf{x}_i - \mathbf{x}_K\|).$$

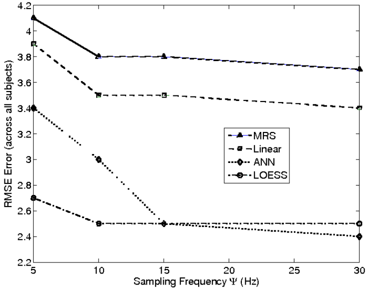
- estimate the coefficient $\boldsymbol{\beta}$ via WLS.

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \sum_{i=1}^{K-L} w_i(\mathbf{y}_i - \sum_{q=1}^{Q} \beta_q z_q(\mathbf{x}_i))$$

Nonparametric: ANN, ANFIS



Performance of deterministic regression

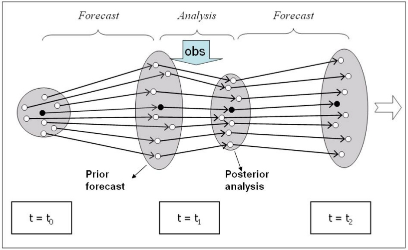


600*ms* lookahead length, RPM relative displacement.

- ANN: more flexible, favorable with abundant training samples.
- LOESS: more specific functional form, more robust with sparse samples, computationally efficient.

Outline

Starting from KF

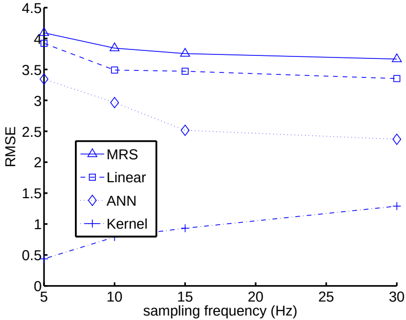


- iterates between predicting and updating the R.V. dist.
- the performance limitation of KF in respiratory prediction lies in linearity, NOT its stochastic nature.
- motivates stochastic estimation with more general dynamic model promising.

What about stochastic regression

A recent development

- admits the random state, relaxes requirement for map consistency.
- nonparametrically learns distribution.



Outline

	deterministic		stochastic	
	samp. path	**regression**	**process**	**regression**
utilize periodicity	needs work	Y	needs work	Y
nonunif. sample	Y	N	Y	N
local variation	needs work	N	Y	Y
cont. prediction	Y	N	Y	N
accuracy	Y	Y	needs work	Y

Summary

- Motion prediction is a challenging problem - a lot of room for improvement.
- Different interpretations/perspectives offer new opportunities.
- Proper choice depends on specific applicationl
- Play with different modifications, combinations and have fun!

Thank you!