Research Statement

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My research interests are in detection and estimation problems in image and video processing, statistical signal processing and computer vision. In particular, my research focus has been on (a) particle filtering methods and change detection in nonlinear systems and (b) shape dynamical models and their applications in computer vision and medical image processing. I have also worked on infra-red image compression and on subspace methods for image classification and their error analysis. Other areas of interest include information theory for detection/estimation problems, watermarking and distributed video coding.

My research discussed below could benefit a lot from collaborations with mathematicians working in stochastic filtering and differential geometry, as well as with experts in neural signal processing, biology and medicine and information theory.

Particle Filtering for Change Detection and Changed Parameter Estimation

Optimal filtering for state space models has numerous applications in signal processing, controls, computer vision, telecommunications and finance. The well known Kalman filter provides a closed form solution for linear Gaussian systems. Many extensions of the Kalman filter based on linearization techniques, have been proposed for nonlinear systems but all of these are unstable, i.e. the error tends to accumulate over time. Particle filters are sequential Monte Carlo methods that approximate the nonlinear filter with a finite number of particles and have been shown to be asymptotically optimal. Change detection for linear systems has been studied extensively. But in many practical problems arising in abnormal activity detection in video, fault detection, congestion detection, and target tracking, the underlying system can be modeled accurately using a nonlinear state space model. Until recently, linearization and change detection methods for linear systems have been the main tools. In recent literature, some algorithms for sudden change detection in nonlinear systems using a particle filter have been proposed. But most of these are for the case of known change parameters and all of these detect only sudden changes.

In my work, I have proposed a statistic called ELL for slow change detection when change parameters are unknown. ELL is the conditional Expectation of the negative Log Likelihood of the state given past observations. This can also be interpreted as the Kullback Leibler distance (plus a constant) between the posterior and prior state distributions. Drastic changes, which ELL fails to detect, are detected using the likelihood of the current observations conditioned on past observations (OL). Using results from stochastic filtering literature, I have shown the following. (a) Stability and monotonic decrease of the errors in approximating ELL for changed observations using a particle filter that is optimal for the unchanged system; (b) The upper bound on ELL error is an increasing function of the “rate of change” with increasing derivatives; and (c) A qualitative result showing complementary behavior of ELL and OL for slow and drastic changes. The second result justifies the experimental observation that ELL detects slow changes very well but fails completely for drastic changes. Experimental results for abnormal activity detection and change detection in bearings-only tracking have been presented.

Future Directions:

Change Detection Applications and Performance Analysis: I have used the ELL statistic for slow abnormality detection in landmark shape dynamical models, with application to abnormal activity detection and detecting motion disorders in human actions. It can also be used for activity segmentation (discussed later). I am collaborating with the neural signal processing group at Maryland to explore the application of ELL and OL for detecting and tracking changes in the spectrotemporal receptive fields (STRFs) in the auditory cortex. Another application of ELL that is being explored along with the acoustic signal processing group at Georgia Tech, is for detecting changes in the system model for direction-of-arrival tracking. Other possible applications of ELL are in network congestion detection, since congestion often starts as a slow change.

I would like to extend my theoretical results to obtain bounds on detection delay for different rates of change. I am also working on the performance analysis of a modification of the cumulative sum (CUSUM) algorithm applied on ELL and OL and its comparison with traditional CUSUM for unknown change parameters.

Implication of Theoretical Results for Particle Filter Design: The stability result for ELL error can be generalized to show stability and monotonic decrease of the error in approximating the posterior expectation of any function of the state (not just ELL) using a particle filter with system model error, as long as the error lasts for a finite time and the unnormalized filter kernel is “mixing”. Asymptotic stability can be shown under stronger assumptions. These
results can be used to analyze and design stable particle filtering algorithms for many practical applications. In a similar fashion, the second result can be generalized by replacing “rate of change” with “system model error per time step” and “ELL” by “posterior expectation of any function of the state”. Implications of this result for design of particle filters under incorrect system model assumptions, will be an important component of my future research. For e.g., it justifies the well known fact that assuming a more general system model results in better average performance, when the system model could be changed. My long term goal is to come up with practically usable results for choosing the number of particles, $N$, for particle filtering under system model error.

**Changed Parameter Estimation:** In most practical problems, the system model is slowly time varying. Since ELL can detect a slow change before the particle filter loses track, it can be used to detect when the system model parameters have changed enough to be learnt again. In recent literature, many algorithms for static parameter estimation using particle filters have been proposed and these can be used for estimating the changed parameter. Two interesting algorithms are Papavasiliou’s method which is proved to be asymptotically stable for “mixing” state transition kernels, and an online EM algorithm proposed by Andrieu and Doucet. I would like to study these methods and how they can be modified for non-“mixing” state transition kernels (which occur in many changing parameter estimation problems). Also, it would be interesting to study the stability of the error in the changed parameter estimate as well as of the particle filtering error.

**Dynamical Models for Filtering Landmark Shapes and Continuous Curves**

Shape analysis is of great practical importance in a wide variety of disciplines such as computer vision, biology, medicine, archeology and geography. In particular, landmark shape analysis focuses on the shape of a configuration of discrete points called “landmarks”. The “shape” of a “configuration” of landmarks was first defined by Kendall as all the geometric information that remains when translation, scale and rotation effects (“global motion”) are removed. There has been a lot of work on statistical analysis of datasets of shapes. Many probability distributions on shape spaces and on their tangent spaces have been proposed. These have been used for shape classification with applications in biology and medicine, for e.g. distinguishing between MRI scans of the brain of normal and schizophrenic patients.

The goal of my Ph.D. research was to model “activity” performed by a group of moving and interacting objects. We proposed to treat each object as a point (“landmark”) and modeled the changing configuration of objects as a moving and deforming shape. The objects could be people or cars or different rigid components of the human body. A state space model was defined, with the objects’ “configuration” as a noisy observation vector and the corresponding “shape” and “global motion” as the hidden state. We proposed to model “shape” dynamics using a linear Gauss-Markov model on the “shape velocity” (defined in the tangent space to the shape manifold at the current shape). Particle filters were used to estimate the “shape” from the noisy “configurations”. Abnormal activity was defined as a slow or drastic change in the system model, with unknown parameters. This motivated the change detection research described above. A stationary “shape activity model” was defined for a surveillance problem of modeling normal behavior of a group of passengers deplaning and moving towards an airport terminal and detecting abnormality. Nonstationary shape activity models were used for a medical application of tracking human actions and detecting motion disorders as abnormalities.

**Future Directions:**

**Activity Segmentation and Unsupervised Learning:** Sequences of different activities each of which is stationary, have been modeled by piecewise stationary “shape activity models”. The activity segmentation problem - breaking a long sequence into stationary pieces - can be tackled by tracking using this model and using ELL to detect segmentation boundaries. The changed parameter estimation algorithms described earlier can be used to learn the parameters for each stationary piece.

The observations of landmark configurations could be obtained using any sensor - video, acoustic, radar or infrared and hence our framework can be applied in many different domains. I would like to explore its applications in robot formations’ control.

**Time Varying Number of Landmarks:** One problem in the current framework is that it cannot be used when the number of landmarks varies with time. But this is required very often in practical problems, either because the number of moving objects (treated as landmarks) changes over time or because the the length of the continuous boundary being approximated using landmarks changes (and hence requires a different number of landmarks). This is an issue that I would like to address in my future research.

**Biomedical Image Analysis and Sensor Fusion:** Some of my research has direct applications in biomedical image processing. 2D and 3D landmark shape analysis has been used very frequently for biomedical image analysis.
The points of interest (to the practitioner) are represented using landmarks. One possible application of our work is for building dynamical models for disease progression, for e.g. models for the growth of tumor in a particular kind of cancer, by using X-rays of a large set of patients over time. Another application is to extend the tools developed by us to segment 3D MRI data. Also, it is easy to extend our framework to fuse observations obtained from different sensors e.g. ultrasound images, X-rays and MRI scans.

**Filtering for Continuous Curves Using Level Set Methods:** I am now studying implicit representations of continuous curves as zero level sets of a higher dimensional function. These do not have the above problem and also can deal with more complicated changes in curve topology over time. Level set methods have been used successfully in segmentation and registration problems in medical images. We are working on a particle filtering algorithm for tracking deforming objects using a level set representation of the curve. The level set representation is infinite dimensional and hence the main challenge here is how to define a stochastic state space model for the curve deformation. Most past work on shape filtering, including my own work, is for parametric representations of curves, which are finite dimensional and hence it is easy to add noise in the deformation model. I would like to explore using time-varying finite dimensional approximations of the curve as the state vector. But the observation is represented using the infinite dimensional level set representation. My idea is to update the finite dimensional basis of the state space (both the dimension and the basis) used to approximate the curve whenever the current approximation is unable to “track” the observations with sufficient accuracy. Two possibilities for approximating the curve are a landmark representation or principal components of possible variations of the curve for a particular application.

Also, we are studying existing work on Riemannian distances on the space of continuous curves and finding practical algorithms to evaluate “mean” and principal submanifolds w.r.t. these distances. This has application in shape classification and clustering, both of which are important problems in medical image analysis.