Application of On-line System for Monitoring and Forecasting Surface Changes for Korean Peninsula

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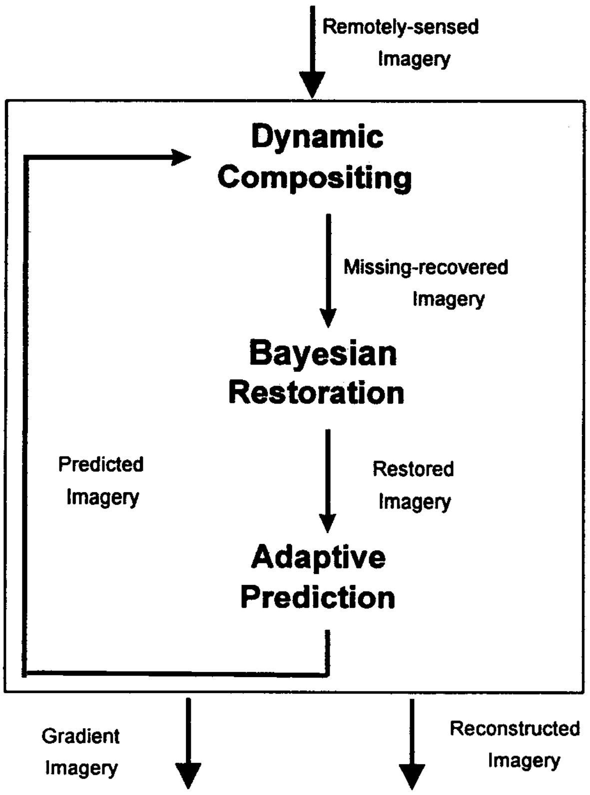
ABSTRACT - This study applies an on-line system, which employes an adaptive reconstruction technique to monitor and forecast ocean surface changes. The system adaptively generates an appropriate synthetic time series with recovering missing measurements for sequential images. The reconstruction method incorporates temporal variation according to physical properties of targets and anisotropic spatial optical properties into image processing techniques. This adaptive approach allows successive refinement of the structure of objects that are barely detectable in the observed series. The system sequentially collects the estimated results from the adaptive reconstruction and then statistically analyzes them to monitor and forecast the change in surface characteristics.

INTRODUCTION

The adaptive reconstruction system combines three filters, as shown Figure 1. Given an observed image as an input signal to the system, the dynamic-compositing filter recovers missing and values in the image by fitting the data to temporal trend in previous history. Using the recovered image, the original image is restored in the modified anisotropic diffusion restoration filter. The adaptive temporal coefficient estimation filter updates the

Figure 1. Adaptive Reconstruction System



parameter of temporal trend for the next iteration. The parameters estimated in the adaptive polynomial coefficient estimation filter for each pixel represents a local temporal trend of the mean signature related only to the target characteristics in recent observation. Using these estimates, the reconstruction system generates a series of images at regular time intervals and forecasts the scene at future time steps. In this study, a Gibbs Random Field (GRF) is used to represent the spatial dependency of the digital image structure, while a polynomial model is employed to track the underlying variation through time. Because simultaneous modeling of the spatial and temporal components is extremely complex, the feedback scheme using multiple filters is utilized to separate the operations on these components. An anisotropic diffusion approach is employed to restore mean intensity image from spatially-contaminated observation. This approach is an iterative smoothing technique which adaptively selects the GRF coefficients according to the intensity difference between the center and neighbor pixels at each iteration. Temporal variation in remotely-sensed image process is represented with a polynomial time series model. For a realization sequence of the intensities, the estimates of the polynomial coefficients are sequentially updated over time using the exponentially weighted least squares criterion. The parameter values related to the class characteristics continuously change over time. An unsupervised classification method is thus applied for the multitemporal analysis. The integrated system sequentially collects the estimated results from the individual filters and then statistically analyzes them to monitor and forecast the change in surface characteristics.

IMAGE MODEL

Most physical processes observed in remote sensing data usually exhibit systematic trends in properties over a long period time. This type of variation is most apparent in the mean intensity. In this study, the mean intensity variation is represented by a polynomial function of time. Let $\mathbf{X}_t$ and $\boldsymbol{\mu}_t$ be the variables of the observed intensity image and the mean intensity image at time t respectively. The image process of n pixels can be modeled as

$$\mathbf{X}_t = \boldsymbol{\mu}_t + \mathbf{e}_t$$
$$\boldsymbol{\mu}_t = \left\{\mu_{t,i} \mid \mu_{t,i} = \sum_{k=0}^{p} a_{i,k} t^k, i \in \mathbf{I}_n\right\} \tag{1}$$

where $\mathbf{I}_n = \{1,2,\cdots,n\}$ be a set of indices of pixels and $\mathbf{e}_t$ is a Gaussian random noise with zero mean.

This study uses a particular class of GRF to represent the spatial dependency of the mean intensity process in neighboring regions. The energy function of the GRF is expressed in terms of "pair potentials" [1] which are a family of symmetric functions

$$\left\{V_{(r,s)}(\boldsymbol{\mu}) \mid V_{(r,s)} = V_{(s,r)} \text{ and } V_{(r,s)} = 0 \text{ if } r = s, (r,s) \subset \mathbf{I}_n\right\}.$$

The pair potential, which is only dependent on the values of pixel pair in the associated clique, can be defined as a function of the quadratic distance between the mean intensities of the associated pixel-pair:

$$V_{(r,s)}(\boldsymbol{\mu}) = \alpha_{rs}\left(\mu_r - \mu_s\right)^2 \qquad 2)$$

where $\alpha_{rs} = \alpha_{sr}$ is the nonnegative coefficient which represents "bonding strength" between the rth and sth pixels. Specification of the energy function with the pair potentials of (2) quantifies the local smoothness in the image spatial structure such that neighboring pixels have closer intensity levels with higher probability. The related GRF defines a probability structure of the mean intensity process:

$$P(\boldsymbol{\mu}) = \kappa^{-1} \exp\left[E_p(\boldsymbol{\mu})\right]$$
$$E_p(\boldsymbol{\mu}) = \sum_{(r,s)\in \mathbf{C}} \alpha_{rs}\left(\mu_r - \mu_s\right)^2 \tag{3}$$

where κ is a normalizing constant and $\mathbf{C}$ is the set of cliques.

BAYESIAN MEAN INTENSITY ESTIMATION USING ANISOTROPIC DIFFUSION

For a probability structure of $\boldsymbol{\mu}$, a class of Gibbs measures is specified with the energy function $E_p(\boldsymbol{\mu})$ of (3) which can be expressed for the periodic boundary as

$$E_p(\mu) = \mu'\mathbf{A}\,\mu$$

where $\mathbf{A}=\{A_{ij},\ i,j\in\mathbf{I}_n\}$ is the matrix related to the bonding strength coefficients such that

$$A_{ij} = \begin{cases} \sum_{k\in R_i} \alpha_{ik}, & \text{if } j=i \\ -\alpha_{ij}, & \text{if } j\in R_i \\ 0 & \text{otherwise} \end{cases}$$

where R_i is the index set of neighbors of the ith pixel. Given the random noise variance Σ = diagonal$\{\sigma_i^2,\ i\in\mathbf{I}_n\}$, the posterior probability of the mean intensity conditioned on the observation process $\mathbf{X} = \mathbf{x}$ is then

$$f(\mu|\mathbf{x}) \propto \exp\left[(\mathbf{x}-\mu)'\,\Sigma^{-1}(\mathbf{x}-\mu) + \mu'\mathbf{A}\,\mu\right],$$

and the log likelihood equation is

$$\Sigma^{-1}(\mathbf{x}-\mu) - \mathbf{A}\,\mu = 0. \tag{4}$$

Equation (4) can be rewritten as

$$\mu = \mathbf{D}^{-1}\mathbf{S}\,\mu + \mathbf{D}^{-1}\Sigma^{-1}\mathbf{x} \tag{5}$$

where

$$\mathbf{D} = \left\{D_{ij},\ i,j\in\mathbf{I}_n \,|\, D_{ii} = \sigma_i^{-2} + A_{ii} \text{ and } D_{ij} = 0 \text{ for } i\neq j\right\}$$

$$\mathbf{S} = \left\{S_{ij},\ i,j\in\mathbf{I}_n \,|\, S_{ii} = 0 \text{ and } S_{ij} = A_{ij} \text{ for } i\neq j\right\}$$

Applying an iterative approach similar to the point-Jacobian iteration method [2] to (5), the mean intensity image is iteratively obtained. At the hth iteration,

$$\hat{x}_i^h = D_{ii}^{-1}\left(\sigma_i^{-2} - \sum_{j\in R_j} S_{ij}\hat{x}_j^{h-1}\right),\ \forall\, i\in\mathbf{I}_n .$$

This iteration converges to a unique solution since

$$D_{ii}^{-1}\sum_{j\in R_j} S_{ij} < 1,\ \forall\, i\in\mathbf{I}_n .$$

Unfortunately the bonding strength coefficients $\{\alpha_{rs},\ (r,s)\in\mathbf{C}\}$are unknown in most practice. This study employs an approach of anisotropic diffusion [3] which adaptively choose the coefficients at each iteration. The coefficients are updated at every iteration as a function of the brightness gradient:

$$\alpha_{rs}^h = g\left(\left|\nabla_{rs}X_{rs}^h\right|\right) = g\left(\left|x_r^h - x_s^h\right|\right),\ \forall\,(r,s)\in\mathbf{C} .$$

As in [3], two functions generating different scale-spaces are considered for $g(\cdot)$:

$$g(\nabla X) = \exp\left[-\left(\frac{|\nabla X|}{K}\right)^2\right] \text{ and } g(\nabla X) = \frac{1}{1+\left(\frac{|\nabla X|}{K}\right)^2}$$

where K is a constant which determines the magnitude of discontinuities to be preserved during the smoothing process. The one privileges high-contrast discontinuities over low-contrast ones, while the other privileges wide regions over smaller ones.

ADAPTIVE POLYNOMIAL PREDICTION

If the mean intensity process is only signal-dependent, the intensity variable can be considered separately for each pixel. Given a realization sequence $\{\mu_\tau,\ \tau = \tau_0, \tau_1, \cdots, \tau_k\}$ and a weight factor for the unit time, $0 < \lambda \leq 1$, the estimate of the polynomial coefficients are sequentially updated over time using the exponentially weighted least squares criterion [5]: for $k \geq p$

$$\left(\hat{a}_{t_k,0}\ \hat{a}_{t_k,1}\cdots\hat{a}_{t_k,p}\right)' = \begin{bmatrix} \phi_0(t_k) & \cdots & \phi_p(t_k) \\ \vdots & \ddots & \vdots \\ \phi_p(t_k) & \cdots & \phi_p(t_k) \end{bmatrix}^{-1} \begin{pmatrix} \varphi_0(t_k) \\ \vdots \\ \varphi_p(t_k) \end{pmatrix} \tag{6}$$

and $k \geq 0$

$$\phi_j(t_k) = \lambda^{(t_k - t_{k-1})}\phi_j(t_{k-1}) + t_k^j, \qquad j = 0,\cdots,2p$$

$$\varphi_j(t_k) = \lambda^{(t_k - t_{k-1})}\varphi_j(t_{k-1}) + t_k^j \mu_{t_k}, \quad j = 0,\cdots,p$$

where $\phi_j(t_{-1}) = \varphi_j(t_{-1}) = 0, \forall j$. Using the estimated coefficients, the mean at the present time can be predicted on the basis of the temporal trend in previous history.

DYNAMIC COMPOSITING

Image compositing is a procedure in which geographically registered data sets which are collected over a sequential period time are compared and the best value of a defined measurement is selected to represent the conditions observed during that time period. Successively observing images from the same area over time, the compositing procedure can be dynamically done by fitting observations to the adaptive polynomial functions of (6). At time t_k, the fitted value for a pixel is

$$\tilde{x}_{t_k} = \sum_{i=0}^{p} \tilde{a}_{t_k,i} t_k^i$$

where $\left(\tilde{a}_{t_k,0}\ \tilde{a}_{t_k,1}\cdots\tilde{a}_{t_k,p}\right)'$ is computed by substituting $\tilde{\phi}$ and $\tilde{\varphi}$ for ϕ and φ in (6):

$$\tilde{\phi}_j(t_k) = \tilde{\lambda}_{t_k}\phi_j(t_{k-1}) + t_k^j$$

$$\tilde{\varphi}_j(t_k) = \tilde{\lambda}_{t_k}\varphi_j(t_{k-1}) + t_k^j y_{t_k}$$

where $\tilde{\lambda}_t$ is a compositing factor and y_t is the present observation. Factor $\tilde{\lambda}_t$ indicates a tradeoff between information in the present value and temporal tendency. As a compositing technique, $\tilde{\lambda}_t$ is set to relatively a small value if data is good, while a larger $\tilde{\lambda}_t$ is used if necessary to achieve consistency with temporal trend. For a missing pixel, the predicted value from the polynomial function or the spatially-interpolated value [4] can be used for y_t.

MONITORING AND FORECASTING SYSTEM

Given an observed image as an input signal to the system, the system initially performs the dynamic compositing, and the mean image is then restored by the Bayesian estimation. Next, the adaptive polynomial coefficients are updated using the reconstructed results. For the Bayesian estimation of the mean intensity process, the variance matrix can be adaptively estimated in the integrated system using the composite values and the restored values.

The estimated polynomial parameters for each pixel represents a local temporal trend at the corresponding site for the mean signature related only to the target characteristics. Using these estimates, an image series with regular time interval can be generated. If a feature is shifting over time, temporal variation of the response in a image series is more rapid at the sites around its boundary. Therefore, the pixels associated with the track of the feature's boundary have relatively steeper temporal trends compared to the inner regions. The amount of temporal trend change in a pixel can be represented by gradient that is the first derivative with respective to time for the estimated polynomial function. The gradient image shows the trace of the feature movement in recent observations, thereby resulting in predicting the future track of target feature.

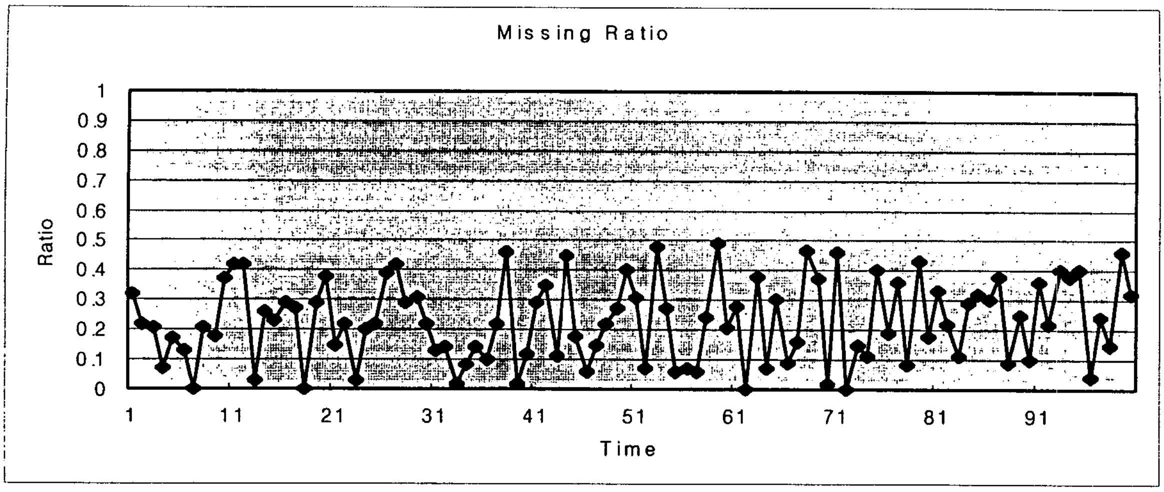


Figure 2. Missing Ratios in Simulated Observation Series at Each Time Step.

EXPERIMENTS

A sequence of images for 100 time steps was generated using the image model of (1). This sequence includes an object which are moving with time-varying characteristics. Each image in the sequence was simulated with the missing ratio of average 25 %. Figure 2 shows the ratios of missing values for 100 time steps. The adaptive reconstruction system was applied to them. The results are illustrated in Figure 3. As in the results, the series of gradient imagery clearly shows temporal track of moving feature.

REFERENCES

[1] H.O.Geergii, *Canonical Gibbs Measure*, Springer-Verlag, Berlin, 1979.

[2] R.S.Varga, *Matrix Iterative Analysis*, Prentice-Hall Inc., 1962.

[3] P.Perona and J.Malik, "Scale-space and edge detection using anisotropic diffusion," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 12, pp. 629-639, 1990.

[4] S. Lee, M.M.Crawford and S. Gallegoes, "Statistical reconstruction and feature tracking of temporally irregular data sequences," *Proc. IGARSS*'95, vol. 1, pp352-354, Firenze, Italy.

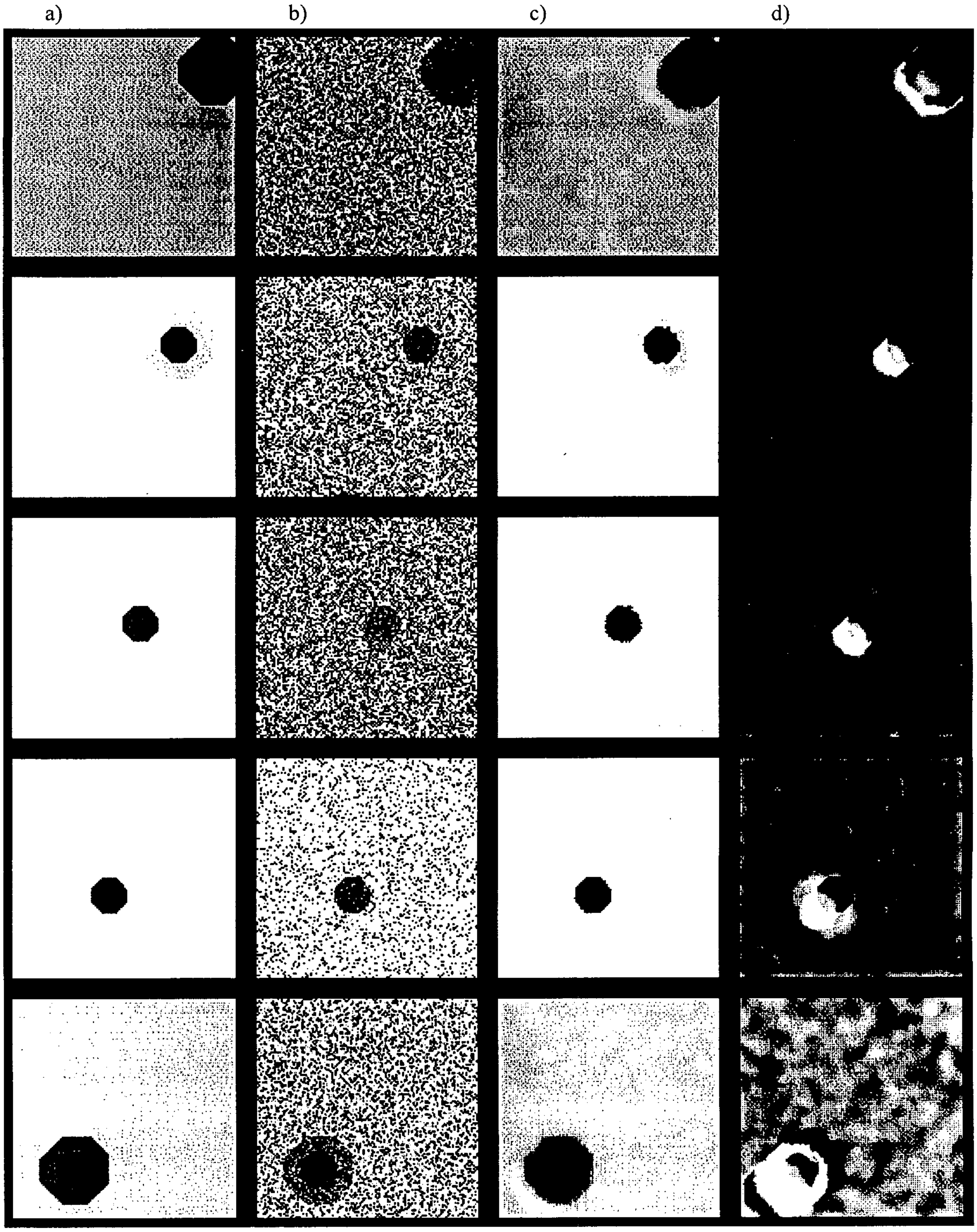


Figure 3. Reconstructed Results of Simulated Series of 100 Images with Time-varying Moving Object

a) Original Pattern Series
b) Observed Series with Missing Values
c) Reconstructed Series
d) Gradient Image Series