Adaptive Spatial-Temporal Image Processing Techniques and Applications to Clutter Rejection in Remote Sensing

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How it Works:
Image Estimation, Clutter Removal and Target Detection

High quality linear and nonlinear spatial-temporal filtering of non-homogeneous in space and non-stationary in time background (suppression below the level of sensor noise)

Input frame: CNR ~ 1000
S(C+N)R ~ 0.02
LOS jitter amplitude ~ 0.5 pix

• Extraction (optimal detection and position estimation) of low-intensity moving objects (cars, ships, aircrafts, missiles, etc.)

• Output frame and signal extraction:
  • CNR ~ 1
  • S(C+N)R ~ 10 - 20
  • position error < 0.05 pix
Advanced Spatial-Temporal Image Processing Techniques

- **Problem and Core Technology**
  - Need to improve performance of existing clutter rejection and target tracking systems
  - Key application: detection and tracking of weak, small targets in heavy clutter with sensors on moving platforms
  - E.g., for efficient ballistic and cruise missile defense with passive space-based and airborne sensors

- **Existing Solutions and Limitations**
  - Present spatial and simple differencing clutter rejection techniques do not allow for clutter suppression to the sensor noise level, which is necessary for efficient target detection/tracking
  - Temporal processing can not be used effectively due to poor image alignment (sub-pixel stabilization issues)
  - Expensive mechanical stabilizers and electronic stabilization
  - New idea and novel algorithmic implementation: use clutter itself for stabilization

- **Potential Benefits**
  - Much better system performance and potential savings due to relaxation for expensive stabilization systems (millions of dollars)
  - The technology is software based and runs on a PC but can also be implemented into FPGA to make it real time with high frame rates and large images (1024x1024)
Structure of the System

Clutter Rejection (CLUR) and Image Stabilization System with Auto-selection and Adaptive Reconfigurable Architecture

- Bank of Spatial-Temporal CLUR and Stabilization Filters
- Estimation / Compensation of Strong Signals
- Clutter/Target Simulator
- Raw Data
- Whiten Data

Graphical User Interface (GUI)

Detection and Tracking System

- Detection and Track-Before-Detect
- Track Initiation, Confirmation and Deletion
- Tracking
- Target Identification / Classification

Preview of Results
Two Different Scenarios of Interest

- **Quasi-stationary Conditions:**
  - Geostationary Orbit
  - Only translations should be estimated and compensated for stabilization
  - There is no non-stationarity due to sensor motion (only due to sensor vibrations)

- **Non-stationary Conditions:**
  - Any orbit (high elliptic, low earth, aircraft, etc.)
  - Rotations should be taken into account: requires 3D stabilization techniques
  - Nonstationarity due to sensor motion and other effects: requires nonstationarity prediction
  - Nonlinearity of earth imprint
  - Sometimes cannot suppress clutter to the noise level even with all sacrifices: novel nonlinear filtering based track-before-detect algorithms are needed
Clutter Rejection and Scene Stabilization:
The Problem

- **OBSERVATIONS:** the sequence of 2D frames

\[ Z_n(r) = \sum_{m=1}^{K_n} I_{m,n} S_n(r + r_n(m) + \delta_n(r)) + b_n(r + \delta_n(r)) + \xi_n(r), n = 1, 2, ..., \]

- \( \xi_n(r) \) – sensor noise,
- \( b_n(r) \) – clutter (background),
- \( I_{m,n} S_n(r) \) – signal from the \( m \)-th target (with the intensity \( I_{m,n} \))
- \( \delta_n(r) \) – unknown shift due to jitter,
- \( r_n(m) = (X_n(m), Y_n(m)) \) – coordinates of the \( m \)-th target
- \( r = r_{ij} = (x_i, y_j) \) – the pixel in the plain image with coordinates \((x_i, y_j)\),
- \( i = 1, ..., N_1, j = 1, ..., N_2 \), where \( N = N_1 \times N_2 \) - number of pixels in the frame

- **GOAL:** to build a spatial-temporal (S-T) filter that rejects clutter (suppresses it to the level of noise) and simultaneously compensate the jitter (stabilizes the scene)

- **MAIN STABILIZATION IDEA:** *use clutter – which is always more intense compared to sensor noise. The higher intensity of clutter, the better!*
A Class of Parametric Spatial-Temporal CLUR Filters with Splitting Approximation

- Idea: use a parametric approximation of clutter and estimate iteratively the parameters in the window $T$ along with frame alignment.

- Time-space splitting approximation of clutter:

  $$b_n(r) \approx \sum_{k=1}^{M} \theta_k(n) f_k(r)$$

  where

  $\theta_k(n)$ – unknown (estimated), slowly changing in the window T frames;
  $f_k(r)$ – chosen functions (orthogonal basis: Fourier, wavelets, splines, etc.)

- Then the estimate of clutter has the following form:

  $$\hat{b}_n(r + \hat{\delta}_n(r)) = \sum_{k=1}^{M} \hat{\theta}_k(n) f_k(r + \hat{\delta}_n(r))$$
Initialize: many possible efficient schemes

Typical Step \( n \):

- **Jitter estimation.** The estimate \( \hat{b}_{n-1} \) obtained from the previous step is compared with the n-th frame, and the MD-estimate of jitter is computed as the solution of the nonlinear optimization problem

\[
\hat{\delta}_n (r) = \arg\min_{\delta} \sum_r \{ Z_n (r) - \hat{b}_{n-1} (r + \delta) \}^2
\]

- **Estimation of Parameters.** Having obtained the estimates \( \hat{\delta}_s \) from the previous step, compute the MD estimates of thetas for the n-th frame from the minimization problem

\[
\min_{\theta} \sum_{s=n-T+1}^{n} \left\{ Z_s (r) - \sum_{k=1}^{M} \theta_k f_k (r + \hat{\delta}_s (r)) \right\}^2 \Rightarrow \{ \hat{\theta}_k (n) \}
\]

- **Clutter Estimation and Rejection.** Using the estimates of thetas and deltas, compute the estimate of clutter and the residuals

\[
\tilde{Z}_n (r) = Z_n (r) - \sum_{k=1}^{M} \hat{\theta}_k (n) f_k (r + \hat{\delta}_n (r))
\]
Developed CLUR Algorithms for SBIRS HIGH (geostationary)

- Spatial-only (in-frame) algorithms – “Spat”
- Temporal filtering in a sliding window – “Temp”
- Adaptive spatial-temporal auto-regression – “STAR”
- Two-dimensional Fourier series with double Nyquist rate – “Four”
- Two-dimensional Wavelet series – “Wavelet”
- Spline-based Filters
  - Adaptive regression with bi-linear double-resolution interpolation – “DRBil”:
  - Cubic spline interpolation with double-resolution – “DRspl”:
- Local polynomial approximation – “Pol”
Spatial-Temporal Autoregressive (STAR) Filter With Compensation

- STAR filter uses transformed data with signal compensation form the rectangular spatial window and temporal window:

\[ \hat{b}_n(i, j) = \frac{1}{T(2N_1 + 1)(2N_2 + 1)} \sum_{t=n-T}^{n-1} \sum_{k=-N_1}^{N_1} \sum_{l=-N_2}^{N_2} a_{lk}(n, t) \hat{Z}_t(i + k, j + l) \]

- The vector of coefficients \( a(t, n) = \| a_{kl}(t, n) \| \) is computed to minimize the empirical variance of the filter output:

\[ a(n, t) = \arg \min \sum_{i,j} \left( Z_t(i, j) - \frac{1}{T(2N_1 + 1)(2N_2 + 1)} \sum_{t=n-T}^{n-1} \sum_{k=-N_1}^{N_1} \sum_{l=-N_2}^{N_2} c_{lk}(n, t) \hat{Z}_t(i + k, j + l) \right)^2 \]

- The computations are reduced to solving the equation with the sample covariance:

\[ \sum_{s=n-T}^{n-1} R(t, s) a(t, s) = R(n, T), \quad R_{r,m,k,l}(t, s) = \frac{1}{N_x N_y (2N_1 + 1)(2N_2 + 1)} \sum_{i,j} \hat{Z}_t(i + r, j + m) \hat{Z}_s(i + k, j + l) \]
Evaluation of the Algorithm Quality:
Performance Indices

- **To compare** clutter suppression algorithms we use the following simple indices:
  - **G-factor**: From the point of view of clutter rejection, a good clutter suppression algorithm should minimize the value of
    \[
    G = \frac{\sigma_{out}}{\sigma_N};
    \]
    \[
    \sigma_N \text{ – variance of the sensor noise; } \sigma_{out} \text{ – variance of the output frame}
    \]
  - **Q-factor**: More important is the evaluation of the relative value of the effective signal-clutter+noise-ratio \((S(C+N)R)\), which is equal to 1 in the ideal case (clutter completely suppressed and there is no signal degradation):
    \[
    Q = \frac{SNR(\text{eff})}{SNR(\text{ideal})} = \frac{\left[\sum_{ij} S(i, j)\tilde{S}(i, j)\right]^{1/2}}{\sigma_{out}}
    \]
    \[
    \frac{\sum_{ij} S(i, j)^2}{\sigma_N}
    \]
  - **Jitter estimation MSE**: Errors of jitter estimation have a substantial impact on the performance of clutter suppression algorithms and estimation of target coordinates
Simplest characteristics, which in realistic conditions due to non-Gaussian clutter distribution are not exhaustive, include:

- Variance $\sigma_b^2$
- Spatial correlation coefficient $\rho$ and the corresponding effective radius of spatial correlation $\Delta_b/(1-\rho)$

Three substantially different scenarios have been considered:

- **Scenario 1:** Relatively weak clutter with relatively high spatial variation
  \[ \sigma_b / \sigma_N = 5 - 6; \quad \rho = 0.85 \]

- **Scenario 2:** Moderately intense clutter with very high spatial variation (small correlation)
  \[ \sigma_b / \sigma_N = 26; \quad \rho = 0.2 \]

- **Scenario 3:** Relatively intense (heavy) clutter with high spatial correlation
  \[ \sigma_b / \sigma_N = 78; \quad \rho = 0.95 \]
Evaluation of the Algorithm Quality: Simulation Results

- **Scenario 2:** Moderate clutter with very high spatial variation:
  \[ \text{CNR} = 25.8; \quad \rho = 0.2; \quad T_{\text{mem}} = 20T_0; \quad A_x = A_y = 0.4\Delta_0 \]

- **G-values**

<table>
<thead>
<tr>
<th>Filtering</th>
<th>Spat</th>
<th>Temp</th>
<th>STAR</th>
<th>Wavelet</th>
<th>DRspl</th>
<th>Pol</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>25.8</td>
<td>16.96</td>
<td>1.68</td>
<td>1.08</td>
<td>2.56</td>
<td>1.68</td>
</tr>
</tbody>
</table>

- **Q-values**

<table>
<thead>
<tr>
<th>Target Velocity</th>
<th>No Filtering</th>
<th>Spat</th>
<th>Temp</th>
<th>STAR</th>
<th>Wavelet</th>
<th>DRspl</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2 (p/f)</td>
<td>0.04</td>
<td>0.02!</td>
<td>0.02!</td>
<td>0.27</td>
<td>0.60</td>
<td>0.30</td>
</tr>
<tr>
<td>1.0 (p/f)</td>
<td>0.04</td>
<td>0.02!</td>
<td>0.03!</td>
<td>0.41</td>
<td>0.72</td>
<td>0.38</td>
</tr>
</tbody>
</table>

The best algorithm
## Evaluation of the Algorithm Quality: Simulation Results

- **MSE of jitter estimation** (in units of the pixel size)

  - **Scenario 1**: \( CNR = 5.4; \rho = 0.85; A_x = A_y = 0.4\Delta_0 \)
  - **Scenario 2**: \( CNR = 25.8; \rho = 0.2; A_x = A_y = 0.4\Delta_0 \)
  - **Scenario 3**: \( CNR = 78.4; \rho = 0.95; A_x = A_y = 0.4\Delta_0 \)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Wavelet</th>
<th>DRspl</th>
<th>DRbil</th>
<th>Pol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>0.007</td>
<td>0.036</td>
<td>0.069</td>
<td>0.024</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>0.003</td>
<td>0.021</td>
<td>0.028</td>
<td>0.025</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>0.056</td>
<td>0.014</td>
<td>0.013</td>
<td>0.026</td>
</tr>
</tbody>
</table>

The best algorithm
Results of Experiments:  
Two weak targets (Movies)

- SNR=5, CNR=50, target velocity=0.5pix, jitter=0.5pix, #targets=2

(Click to Play Movies)
Residual jitter is a small fraction of a pixel, usually less than 10% and often 1-2%!
Comparison of a Simple Differencing Method With Our Methods: Results for the Differencing Algorithm

(Click to Play Movie)
Comparison of a Simple Differencing Method With Our Methods: Results for the STAR Filter

Automatic Selection – STAR Filter

(Click to Play Movie)
Nonstationary Conditions:
Low-Earth Orbit and High-Earth Elliptic Orbit Satellites

- While this approach is very effective for quasi-stationary conditions (e.g., geostationary staring sensors), it does not seem completely amenable to other scenarios like low-earth, high-elliptic orbits and aricrafts.

- Therefore, an important direction of the work is to modify described image processing techniques and develop new methods that will be efficient for more difficult, non-stationary environments characteristic of low-earth orbits, etc.

- The clutter rejection method for nonstationary conditions in question requires not only translational and rotational stabilization but also a sophisticated image prediction algorithm.
Specific Features

- **Non-linearity of images**
  - Sphericity of the earth should be taken into account

- **Nonstationarity related to sensor motion**
  - Frame shifts in the FOV (field of view) may be on the order of dozens of pixels, which affects the clutter rejection and stabilization algorithms.
  - As a result, a two-stage stabilization procedure is needed
    - At the first stage, we propose to use a stabilization system that allows for ultra-high speed image stabilization (rotations and translations) reducing jitter to the pixel or sub-pixel level
    - At the second stage, an iterative super-stabilization algorithm developed for geostationary sensors is used to compensate for the remaining instability
Specific Features (Cont.)

- The necessity to identify a 3D cloud cover model
  - For efficient clutter rejection it is necessary to account for a 3D cloud model (altitude relief–shape of clouds).

- Complexity of images and high clutter-to-noise ratio (CNR)
  - For low-orbit sensors, one should take into consideration high CNR and high signal-to-noise ratio (SNR)
  - Complex intensity distribution across frames due to discontinuities of the intensity function on borders of nonhomogenous regions on the earth surface
  - In order to suppress such clutter to the level of sensor noise, new clutter rejection algorithms must be developed

Moderate CNR

High CNR
A Novel Robust Method

- The main features of the novel approach for image estimation are that we account for:
  - Background dynamics due to wind, turbulence, and convection
  - Dynamics of observation conditions related to the motion of observer that causes nonlinear disturbances and warping of cluttered backgrounds that cannot be described by smooth single-valued functions

- The main novelty is prediction of image intensity that changes due to sensor motion
  - Intensity deformations/warping have a quite complex form and have to be described by a discontinuous function
  - To this end, new mathematical techniques are needed; these are much more complex than in the case of the stationary sensor
3-axis Stabilization

(Click to Play Movie)
Clutter Rejection Results:
MeteoSat Data

- **Parameters:** Perigee altitude 500km; Apogee altitude 35800km; pix size 35*10^-4 rad; Input frame 512x512; Output frame 128x128; Frame rate 1 fps

- **CLUR algorithm:**
  - Stabilization: rotational, shifts, scaling
  - CLUR filter: Image prediction based on a parametric model

- **Input and output frames parameters:** Input variance 500; Output variance 5; G=100

(Click to Play Movie)
Benefits/Capabilities

- We anticipate that the developed prototype can be effectively used for the design and optimization of the real system in a variety of conditions (meteorological/illumination) and sensor/platform geometries. In particular, as was discussed above:
  - The algorithms of data processing ensure almost optimum performance of target detection, position estimation and tracking for the most difficult clutter scenarios in the presence of LOS jitter
  - The excellent quality of data processing is achieved due to adaptive selection of the best (for the current background) algorithm of clutter suppression among a set of developed algorithms
  - The algorithms are capable to operate simultaneously with both low intensity signals (S(C+N)R about 0.01) and high intensity signals and outliers, which should be compensated to optimize the performance
- The software imbedded into an interface with visualization constitute powerful tools for the design and optimization of the specific system in specific conditions of interest