Sparse Shape Registration for Occluded Facial Feature Localization

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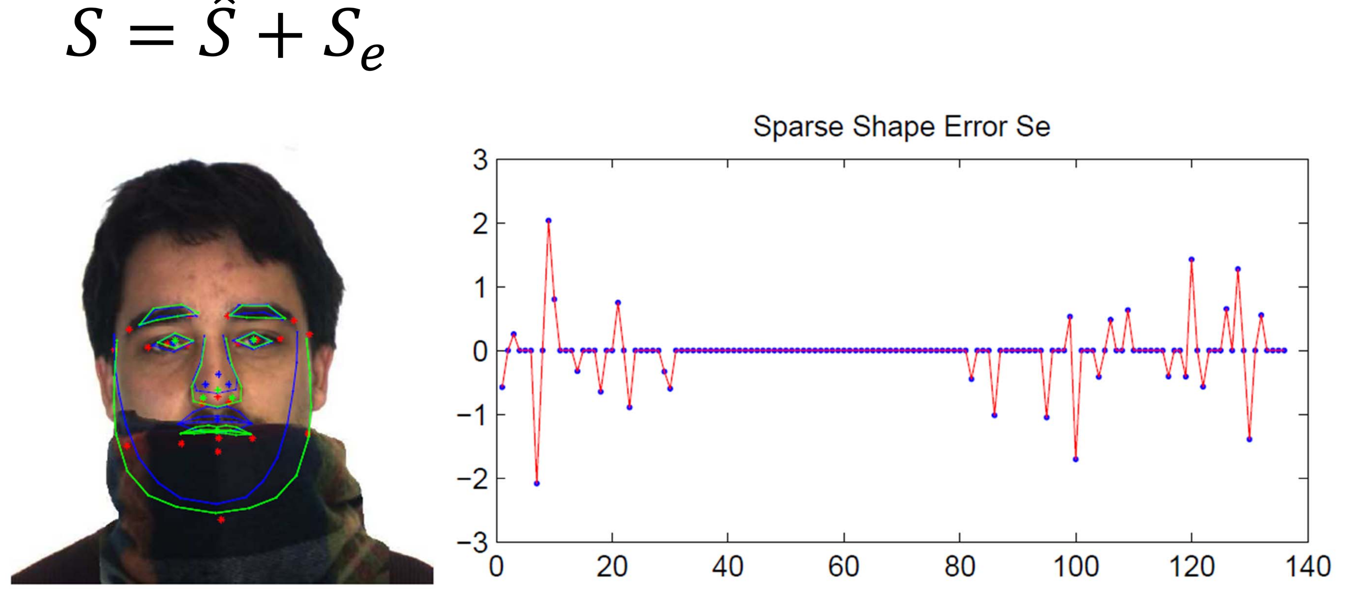
Motivations

- Active Shape Model (ASM) based shape registration approaches assume the residuals between model fit and images have a Gaussian distribution.
- Occluded landmarks lead to incorrect local matches, and may significantly distort the shape matching results.
- Use sparse errors to model the occluded landmarks:

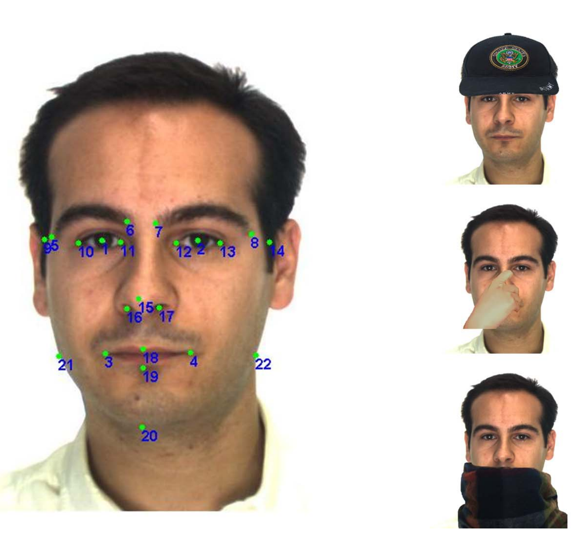
$$S = \hat{S} + S_e$$

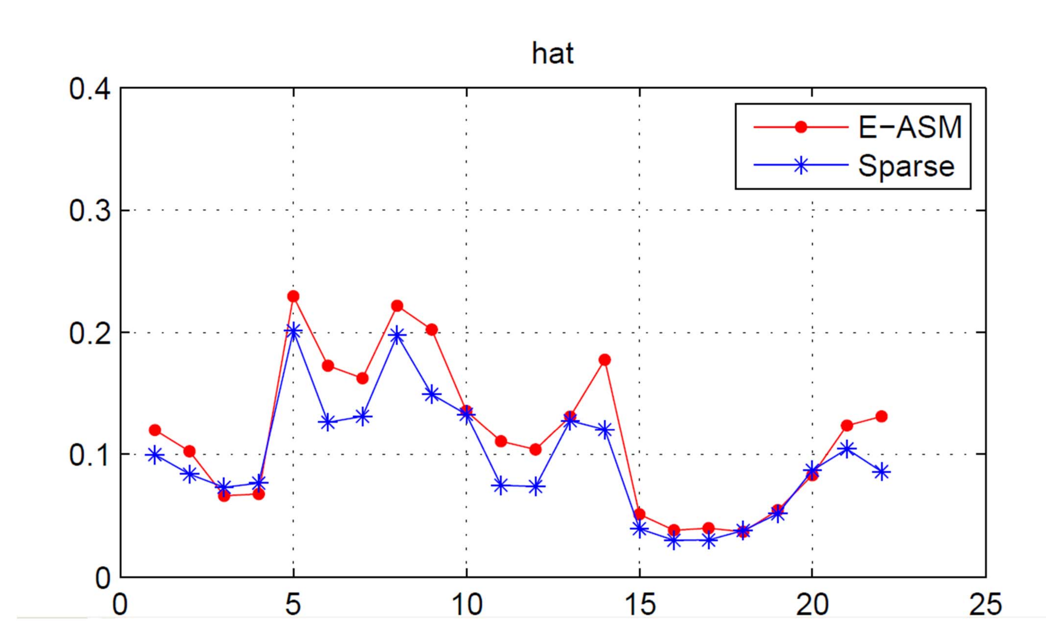


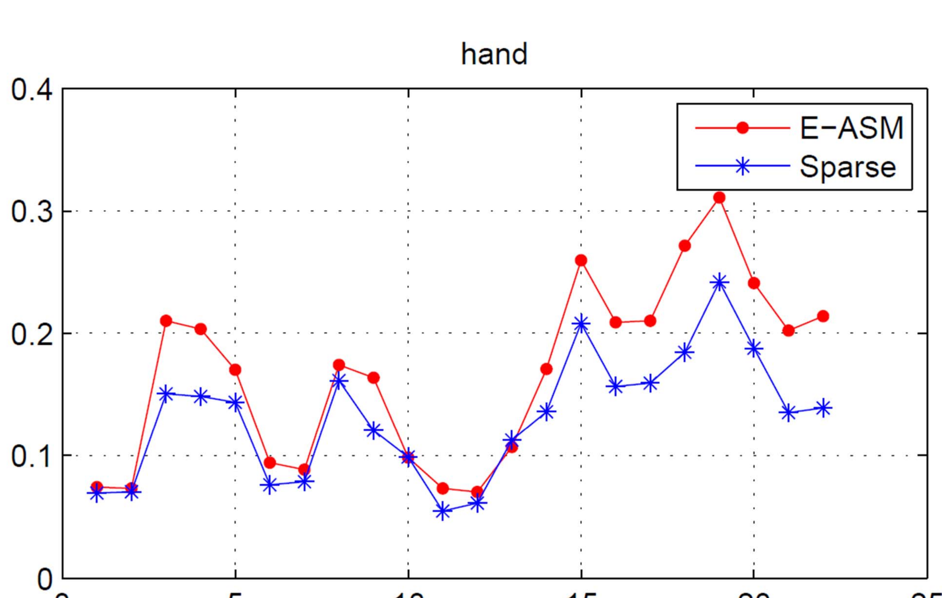
Formularization

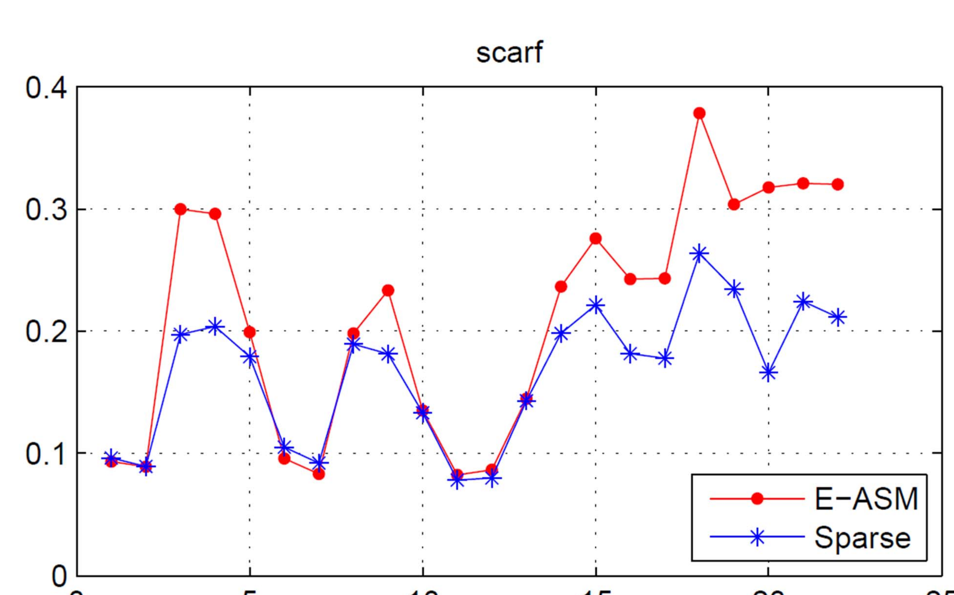
- Minimize the energy function $E = E_b + E_s + E_{S_e} + E_I$
  - Subspace energy term $E_b = \frac{1}{2} b^T \Lambda^{-1} b$
  - Shape energy term $E_S = \frac{1}{2} ||S - Ub - \bar{S}||^2$
  - Sparse error term $E_{S_e} = \lambda \cdot ||W \cdot S_e||_1$
  - Feature error term $E_I = \frac{1}{2} \sum_{i=1}^{N} d(x_i)^2$
- The sum of the first 3 terms is a convex function
- Alternative optimization approach
  - Repeat until converge
    - Minimize the sum of first 3 terms
    - Minimize the 4th term

Experiments









Algorithm Summary

Algorithm 1 *Minimize* $Ep = E_b + E_S + E_{S_e}$

$b^0 = U^T(\hat{S} - \bar{S})$, $S_e^0 = 0$
for $k = 0 : k_{max}$ **do**
  Compute L to be the largest eigenvalue of $\frac{\partial^2 E_p}{\partial b^2}$.
  $b^{k+1} = b^k - \frac{1}{L} \cdot \frac{\partial E_p}{\partial b}$
  $S_e^{k+\frac{1}{2}} = S_e^k - \frac{\partial E_p}{\partial S_e}$
  $S_e^{k+1} = max(|S_e^{k+\frac{1}{2}}| - \lambda, 0) \cdot sign(S_e^{k+\frac{1}{2}})$
end for

Algorithm 2 *Minimize* E_I

for $i = 1 : N$ **do**
  for $k = 0 : k_{max}$ **do**
    Compute $\hat{\nabla} f_{h,K}(\mathbf{x}_i^k)$ using equation (23)
    $\mathbf{x}_i^{k+1} = \mathbf{x}_i^k - \hat{\nabla} f_{h,K}(\mathbf{x}_i^k)$
  end for
end for

Algorithm 3 *Sparse Shape Optimization*

Compute θ using detection result
Initial status $b_0 = 0$, $S_e = 0$, $S = \bar{S}$, $\hat{S} = \bar{S}$, $\hat{S}' = M_\theta(\hat{S})$
repeat
  Run Algorithm 2 to optimize $\hat{S}'$
  Compute transformation parameter θ matching $\hat{S}'$ to $\bar{S}$
  $\hat{S} = M_\theta^{-1}(\hat{S}')$
  Run Algorithm 1 to optimize b and S_e
  $\hat{S}' = M_\theta(\bar{S} + Ub)$
until $\hat{S}'$ converges

Examples