



Building Roadmaps of Local Minima of Visual Models

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Contributions

- Optimization-based algorithms for systematically finding nearby local minima of high-dimensional cost functions, and building ‘roadmaps’ of the low-peak-cost paths linking them.
 - No prior knowledge of minimum distribution or cost topography needed.
 - Can also handle constraints (inequality, non-linear).

Approach

- Adapt computational chemistry methods for finding *Transition States*
 - codimension 1 saddle points (0 gradient, 1 negative curvature direction)
- Two deterministic approaches based on local optimization:
 - Eigenvector tracking:** modified form of damped Newton minimization.
 - Hypersurface sweeping:** propagates a hypersurface through the space, tracking minima on it.
- From each transition we slide downhill to next minimum
 - minimum peak cost pathway linking the minima

Conclusions

- Efficient deterministic algorithms for exploring high-dimensional non-convex likelihood surfaces.
- Useful for many other vision problems (model-based vision, SFM).

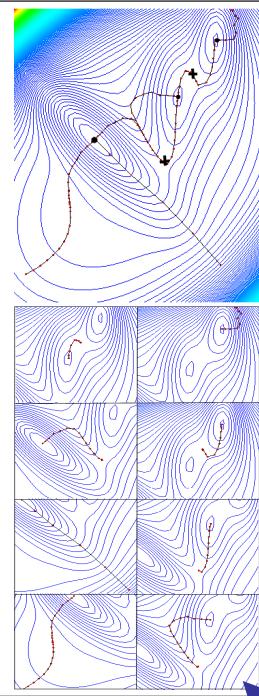
Eigenvector Tracking

- Choose an ascent eigenvector λ' and track it as you progress Move uphill along λ' , and downhill along all other eigenvectors

$$\hat{\delta}\mathbf{x}(\lambda) = \begin{pmatrix} \frac{g_1}{\lambda_1 + \sigma_1 \lambda'}, \dots, \frac{g_n}{\lambda_n + \sigma_n \lambda'} \end{pmatrix}^T, \quad \lambda \geq -\min(0, \sigma_1 \lambda'_1, \dots, \sigma_n \lambda'_n) + \epsilon \quad , \quad \sigma_k = -1, \sigma_{\text{rank}} = +1$$

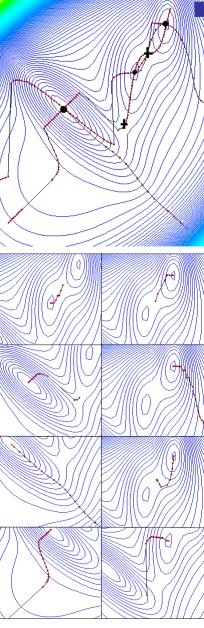
→ Tracking ‘a given eigenvalue’ is ill-defined : when eigenvalues cross, their eigenvectors slew around rapidly.

→ Search may diverge to infinity (wall-climbing).



Hypersurface Sweeping

- A codimension 1 saddle is
 - a local maximum in one direction
 - a local minimum in the other $n-1$ directions
- Sweep space with a moving hypersurface
 - hyperplane, expanding hyper-ellipsoid...
 - parametrized implicitly $c(\mathbf{x}) = r$ or explicitly $x = \mathbf{x}(u, v)$
- Track local-minima within hypersurface and find temporal maxima along tracks
 - Only finds saddles that surface cuts in positive curvature directions
 - Some (‘sawtooth’) maxima are disappearances not saddle points
 - Plane / ellipse orientation fixes initial track directions.



Local Minimization versus Saddle Point Search

- Minimization**
 - many local descent based algorithms
 - measure progress by decrease in function value : local ‘sufficient decrease’ ensures ‘global convergence’ to some minimum
- Saddle Point Search**
 - ascend towards saddle using modified descent algorithms
 - no universal progress criterion
 - needs initial ascent direction or direction weighting

Newton Minimization

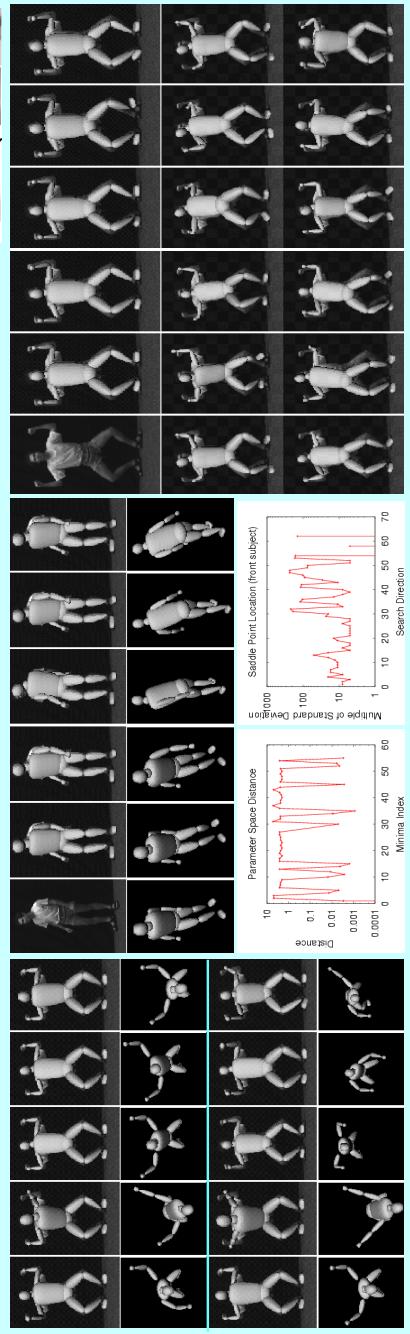
- Pure Newton minimization (f = cost function, g = gradient, H = Hessian)

$$0 = g(x + \delta\mathbf{x}) \approx g(x) + H\delta\mathbf{x} \Rightarrow \delta\mathbf{x} = -H^{-1}g$$
 - efficient near minimum
 - further away, may diverge or converge to any type of stationary point.
- Damped Newton minimization
 - globalize convergence by adding ‘damping’ matrix D
 - $\delta\mathbf{x} = (H + \lambda D)^{-1}g$
 - in an eigenbasis where $D = I :$

$$\hat{\delta}\mathbf{x}(\lambda) = \begin{pmatrix} \frac{g_1}{\lambda_1 + \lambda}, \dots, \frac{g_n}{\lambda_n + \lambda} \end{pmatrix}^T, \quad \lambda \geq -\min(0, \lambda_1, \dots, \lambda_n)$$

Application: Monocular Human Pose, Reconstruction and Tracking Ambiguities

- 32 dof articulat human model with superquadric parts, joint angle limits and part non-interpenetration constraints
- Initialize using model-image joint correspondences, track using edge+silhouette and edge+flow cost.
- Method finds many (~300) minima caused by ambiguous (forwards/backwards) depths or incorrect assignments.
- Many more minima are eliminated by physical (joint, non-interpenetration) constraints



Tracking Ambiguities: flow+edge (top) and silhouette+edge (middle & bottom) cost function