TRACKING FEATURES WITH KALMAN FILTERING, MAHALANOBIS DISTANCE AND A MANAGEMENT MODEL

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  - Kalman Filter;
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Introduction:

- Feature tracking is a complex problem for which computational solutions had evolved considerably in the past decade.
- Applications of motion tracking are usual: surveillance, object deformation analysis, traffic monitoring, etc.
- Some common difficulties are:
  - several features to be tracked simultaneously;
  - appearance/disappearance of features along the image sequence;
  - long image sequences to be processed;
  - etc.
Existing approaches:

- They try to find good compromises between the accuracy of the motion tracking and the involved computational cost.

Examples:

- **Pfinder** (Wren, Azarbayejani, Darell, Pentland, 1997)
  A real-time system for tracking people in order to interpret their behavior. Expects only one user in the image scene and that the scene is quasi-static;

- Bayesian networks simplified by gradually discarding the influence of the past information on the current decisions.

- Tracking with Kalman Filter is a widespread technique for object tracking; although other filters have recently become more usual, they have also revealed some problems too.
Methodology adopted:

- **Kalman Filter** is used to estimate the features’ positions along the image sequence;

- For the matching (data association), between measures (real features) and filter’s estimates, we use Optimization of the global correspondence based on Mahalanobis Distance;

- To deal with the problem of appearance, occlusion and disappearance of the tracked features, we employ a Features’ Management model.
Kalman Filter:

- Kalman Filter is an optimal recursive Bayesian stochastic method, but assumes Gaussian posterior density functions at every time step;
- Erroneous estimations, for instances in problems involving non-linear motion, can be corrected overcome by using adequate approaches in the matching step.
- In this work:
  - the system state is composed by the positions, velocities and accelerations of the tracked features (points);
  - new measurements are incorporated in the system model whenever a new image frame is evaluated.
Matching:

- For each feature estimated, there may exist, at most, one new measurement to correct its estimated position.
- With Kalman’s usual approach, the predicted search area for each tracked feature is given by an ellipse (whose area will decrease as convergence is obtained and vice-versa).

Some problems:

- There may not exist any real feature in the search area or there might be several instead;
- Even if there is only one correspondence for each feature, there is no guarantee that the best set of correspondences is achieved.
Matching:

- We use optimization techniques to obtain the best set of correspondences between predictions and measurements;
- To establish the best global set of correspondences we use the Simplex method;
- The cost of each correspondence is given by the Mahalanobis Distance.

Simplex Method:

- An iterative algebraic procedure used to determine at least one optimal solution for each assignment problem.
Matching:

- **Mahalanobis Distance:**
  - The distance between two features is normalized by its statistical variations;
  - Its values are inversely proportional to the quality of the prediction/measurement correspondence;
  - To optimize the global correspondences, we minimize the cost function based on the Mahalanobis Distance.
Matching:

- **Occlusion/Appearance:**
  - Assignment restriction (1 to 1) not satisfied – problem solved with addition of fictitious variables:
    - Features matched with fictitious variables are considered unmatched;
  - Unmatched tracked feature – it is assumed that the feature has been occluded, but the tracking process is maintained by including its predicted position in the measurement vector although with higher uncertainty;
  - Unmatched measurement – we consider it as a new feature and initialize its tracking process.
Management Model:

- When a feature disappeared of the scene: Is it just occluded? It was removed definitively? Should we keep its tracking?
- This decision is of greater importance if many features are being tracked, if the image sequence is long, if the tracking is in real-time, etc;
- We use a management model in which a confidence value is associated to each feature:
  - In each frame, if a feature is visible then its confidence value is increased, else it is decreased;
  - If a minimum value of the confidence value is reached, then is considered that the feature has definitively disappeared and its tracking will cease (if it reappears, its tracking will be initialized);
  - In this work, the confidence values are integers between 0 and 5, and initialized as 3.
Experimental Results:

- Using synthetic data:
  - Blobs A, B with horizontal translation and C, D with rotation:
Experimental Results:

- Using synthetic data:
  - Continuation ... Blobs C, D invert their rotation direction:
Experimental Results:

- **Using synthetic data:**
  - **Management of the tracked features - blobs (dis)appear randomly:**

![Diagram showing tracking results with features labeled A, B, C, D, E.]

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</table>
Experimental Results:

- Using real data:
  - Tracking 5 blobs in human gait analysis:
Experimental Results:

- Using real data:
  - Tracking mice in a lab environment during 547 frames:
    (with very significant changes in the direction of the motion)
Experimental Results:

- Using real data:
  - Tracking persons in a shopping centre:

  (5 frames interval)
Conclusions:

- We presented a methodology to track features along image sequences based on:
  - Kalman Filter;
  - Optimization techniques;
  - Mahalanobis Distance;
  - A features’ Management Model;
- With our approach, in each image sequence frame, the best set of correspondences is guaranteed;
- Our approach also allows the incorporation of new data even if it would be out of the default Kalman search area (e.g. change in movement direction).
- The used features’ management model allows the tracking with the lowest computational cost possible, as the features simultaneously tracked are continuously update.
Future Work:

- Consideration of other stochastic methods in the motion estimation; like Particle Filters and Unscented Kalman Filter;
- Adoption of matches one to several (and vice-versa);
- The automatic selection of the best dynamic model to use along the image sequence;
- The learning of the dynamic model to use from the image sequences being tracked;
- Use our tracking methodology in human clinical gait analysis.
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The End!
Thank You!