It’s Moving!
A PROBABILISTIC MODEL FOR CAUSAL MOTION SEGMENTATION IN MOVING CAMERA VIDEOS
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GOAL
segmenting a video into static environment and moving objects
• modeling camera motion and object motion
• Bayesian approach: new flow angle likelihood for assigning pixels to a motion model

CAMERA MOTION FIELD

When the camera moves, pixels belonging to the static background no longer maintain their position in consecutive frames. They move accordingly to a translational or/and rotational motion field due to camera motion.

ANGLE FIELD

Top to bottom: the original frame, the observed translational angle field, the best fitting translational camera angle field and the segmentation results using our motion segmentation method. The moving object is shown in red.

Most information about 3D motion direction is contained in the flow field, not the flow magnitude. This is because the flow angle is completely determined by that motion (U,V,W) and location (x,y) in the image (if the camera is only translating), whereas the flow magnitude is a function of the object’s depth.

MODELING MOTION

Left to right: Frame 1 of the video sequence cars2 of the BMS-26 data set; binary ground truth showing static environment in black and moving objects in white and observed translational angle field described by four different motion models. Three of the motion models describe the three differently moving objects the fourth motion model describes the pixel displacement of the static environment due to camera translation.

METHOD

compute flow
compute angle field

compute segmentation
Bayes
compute likelihood

RESULTS

Comparison to state-of-the-art: Matthew’s correlation coefficient and F-measure for each method and data set.

PROBABILISTIC MODEL

BAYES’ RULE
Posterior probabilities of each motion model Mj at each pixel location

\[ p(M_j | v_i) \propto p(v_i | M_j) \cdot p(M_j) \]

FLOW ANGLE LIKELIHOOD

\[ p(v_i | M_j) = \frac{\exp(\mu \cdot \text{atan}2(W-y, V-f, W-x-U-f))}{\sqrt{2\pi} \cdot \sigma} \]

The von Mises distribution. When a motion field vector \( v_i \) is perturbed by added Gaussian noise, the distribution over optical flow angles is well-modeled by a von Mises distribution. The figure shows the best von Mises fit to these sample distributions and the blue curve shows the lower quality of the best Gaussian fit.

The translational magnitudes alone have no information about which motion is most likely. Magnitudes are specifying the informativeness of the flow angles.

We model the flow likelihoods using a von Mises distribution with parameters \( \mu \) and \( \kappa \), where \( \kappa \) depends on the flow magnitude \( |v_i| \).

\[ p(\theta_{v_i} | |v_i|, M_j) \propto \mu \cdot \text{atan}2(W-y, V-f, W-x-U-f) \]

\( \alpha \) and \( \beta \) are parameters, that add flexibility to that model.

PRIOR

We create a prior at each pixel for each motion model in the new frame by propagating the posterior from the previous frame.

M: Motion direction of a motion component projected on the image plane angle field.

\( |v_i| \): observed flow vector containing only motion due to camera translation and object motion.

\( m_h \): flow vector describing the motion field caused by a translating camera in its stationary 3D environment, \( m_h \) does not include motion of independently moving objects.

\[ p(M_j | v_i) \propto \exp(\mu \cdot \text{atan}2(W-y, V-f, W-x-U-f)) \]

\[ p(\theta_{v_i} | |v_i|, M_j) \propto \mu \cdot \text{atan}2(W-y, V-f, W-x-U-f) \]

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\[ \text{compute flow} \]

\[ \text{compute angle field} \]

\[ \text{compute segmentation} \]

\[ \text{Bayes} \]

\[ \text{compute likelihood} \]

\[ \text{Comparison to state-of-the-art: Matthew’s correlation coefficient and F-measure for each method and data set.} \]

\[ \text{PROBABILISTIC MODEL} \]

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Posterior probabilities of each motion model \( M_j \) at each pixel location

\[ p(M_j | v_i) \propto p(v_i | M_j) \cdot p(M_j) \]

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