

PROBLEM STATEMENT



SUM OF GAUSSIAN (SOG) FILTER

• In our SoG filter, we approximate a probability density function $p(\mathbf{x})$ as a combination of G weighted multivariate Gaussians as:

$$p(\mathbf{x}) = \sum_{g=1}^{G} \gamma^g \mathcal{N}(\mathbf{x}^g; \mathbf{P}^g)$$

- The SoG filter exploits a bank of Extended Kalman Filters (EKF). Every of them, it is estimated by means of a prediction-update strategy.
- The weight coefficients are updated every frame, removing those with low factor $\gamma_{k|k}^{g}$.
- An overall mean $\hat{\mathbf{x}}_{k|k}$ and covariance $\mathbf{P}_{k|k}$ for the SoG filter can be considered for visualization:

$$\hat{\mathbf{x}}_{k|k} = \sum_{g=1}^{G} \gamma_{k|k}^{g} \, \hat{\mathbf{x}}_{k|k}^{g}$$
$$\mathbf{P}_{k|k} = \sum_{g=1}^{G} \gamma_{k|k}^{g} \left[\mathbf{P}_{k|k}^{g} + [\hat{\mathbf{x}}_{k|k}^{g} - \hat{\mathbf{x}}_{k|k}] [\hat{\mathbf{x}}_{k|k}^{g} - \hat{\mathbf{x}}_{k|k}]^{\top} \right]$$

SELF-CALIBRATION NON-RIGID SOG

• The state of the camera is represented by a 18-dimensional vector, including calibration $(\alpha, \beta_x, \beta_y, k_1, k_2)$, camera pose r and orientation q, and linear v and angular $\omega^{\mathcal{C}}$ velocities:

 α_{k+1} $\beta_{x_{k+1}}$ $\beta_{y_{k+1}}$ ı $k_{1_{k+1}}$, $\mathbf{m}_{k+1} =$ $k_{2_{k+1}}$ $\mathbf{r}_k + (\mathbf{v}_k + \Delta \mathbf{v}) \Delta t$ \mathbf{r}_{k+1} $|\mathbf{q}_k \times \mathbf{q}((\boldsymbol{\omega}_k^{\mathcal{C}} + \Delta \boldsymbol{\omega}^{\mathcal{C}})\Delta t)|$ \mathbf{q}_{k+1} $\mathbf{v}_k + \Delta \mathbf{v}$ \mathbf{v}_{k+1} $\lfloor oldsymbol{\omega}_{k+1}^{\mathcal{C}}$ $\boldsymbol{\omega}_{k}^{c} + \Delta \boldsymbol{\omega}^{c}$

TOTAL ESTIMATION FROM RGB VIDEO: ON-LINE CAMERA SELF-CALIBRATION, NON-RIGID SHAPE AND MOTION ANTONIO AGUDO

- Given an uncalibrated monocular video where both rigid and non-rigid scenes can be observed.
- We want to jointly and sequentially retrieve the self-calibration of the camera, the 3D non-rigid shape model and the full camera trajectory.
- We propose a Bayesian filtering approach based on a sum-of-Gaussians filter composed of a bank of non-rigid extended Kalman filters. Neither training data nor a calibration pattern are needed.



Feat.	Tracking	Self-Ca	alibration	Р	rocess	Shape				
		Focal	Full	Batch	Sequential	Rigid	Non-R Isometric	igid Elastic		
2, 34]	\checkmark	\checkmark			\checkmark	\checkmark				
6]	\checkmark		\checkmark		\checkmark	\checkmark				
9, 25, 38]				\checkmark		\checkmark	\checkmark	\checkmark		
32]					\checkmark	\checkmark	\checkmark	\checkmark		
	\checkmark				\checkmark	\checkmark	\checkmark	\checkmark		
4, 33]	\checkmark	\checkmark		\checkmark		\checkmark	\checkmark			
urs	\checkmark		\checkmark		\checkmark	\checkmark	\checkmark	\checkmark		

- The state of the scene is represented by a 3ndimensional vector, with n the number of points.
- We use an elastic model based on finite elements, defining a compliance matrix C_k to relate the deformation of all points, and a vector of Gaussian acting forces Δf . For every frame, the state function is:

$$\mathbf{y}_{k+1} \equiv \mathbf{y}_{k+1} \left(\mathbf{y}_k, \Delta \mathbf{f} \right) = \mathbf{y}_k + \mathbf{C}_k \Delta \mathbf{f}$$

- Our model can handle both inelastic and elastic materials, and it is computed every frame.
- A full perspective camera model is assumed.









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CALIBRATION, MOTION AND NON-RIGID SHAPE RECONSTRUCTION

Data	Non-Critical Motion Sequences								Critical Motion Sequences						
	Indoor		Loop Closing		Silicone Cloth		Laparoscopy		Pure Rotation		Pure Translation		Parallel Optical Axis		
	Off-line	On-line (Ours)	Off-line	On-line (Ours)	Off-line	On-line (Ours)	Off-line	On-line (Ours)	Off-line	On-line (Ours)	Off-line	On-line (Ours)	Off-line	On-line (Ours)	
els]	194.10	195.24±1.27	196.90	196.97±0.53	312.89	309.30±0.30	280.91	274.36±0.32	194.10	211.65±12.90	194.10	204.14±4.44	194.10	202.84±8.31	
els]	160.20	$158.94{\pm}0.92$	153.50	$159.14{\pm}1.41$	157.66	$158.60{\pm}0.11$	184.48	166.00±0.18	160.20	158.68±6.07	160.20	156.47±3.48	160.20	158.89±7.08	
els]	128.90	128.85±0.99	130.80	131.22±1.19	121.32	119.21±0.11	133.48	136.06±0.17	128.90	121.48±6.92	128.90	129.14±3.13	128.90	116.51±5.98	
n^{-2}]	.0623	$.0661 {\pm} .0023$.0693	$.0721 {\pm} .0028$.0094	$.0056 {\pm} .0002$.0054	.0078±.0004	.0623	$.0626 {\pm} .0073$.0623	$.0676 {\pm} .0048$.0623	$.0679 {\pm} .0109$	
n^{-4}]	.0139	.0122±.0008	.0109	$.0107 {\pm} .0007$.00011	$.00036 {\pm} .00003$.00026	.0004±.00004	.0139	.0098±.0024	.0139	.0088±.0015	.0139	.0121±.0032	
							1								

Indoor and Loop Closing Sequences

• Non-Critical Motion Scenarios

Hand-held 320 \times 240 camera/endoscope. Rigid and elastic sequences.

Critical Motion Scenarios

Hand-held 320 \times 240 IEEE1394 camera. Scene and/or calibration is not possible.

















Critical Motion Sequences