Markerless Human Motion Capture

Graphics, Vision and Video - Interdisciplinary Topics in Visual Computing Seminar

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Contents

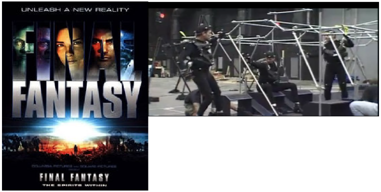
Human Motion Capture

body position capture **performance capture**

process of analysing human movements from video data

Human Motion Capture Applications

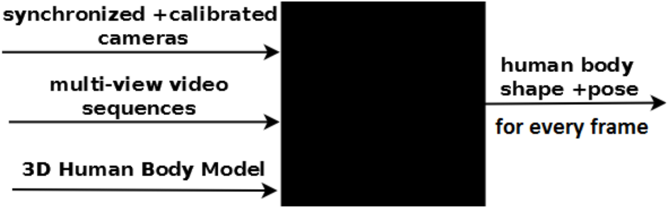
(a) Movies



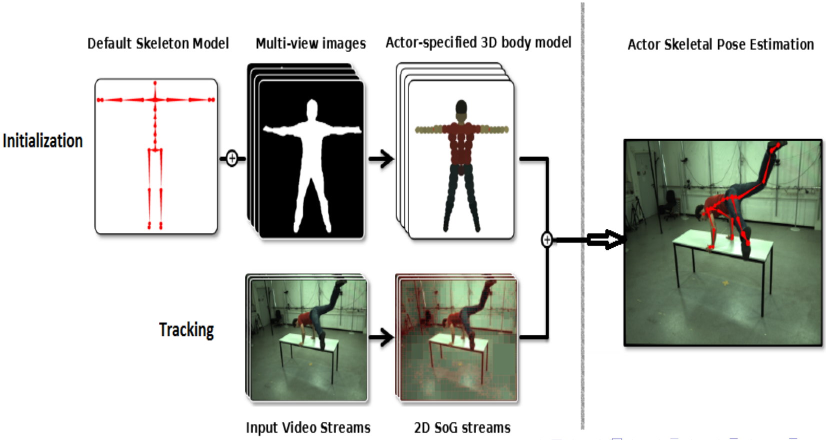
(b) Animation for Games

(c) Sport Science

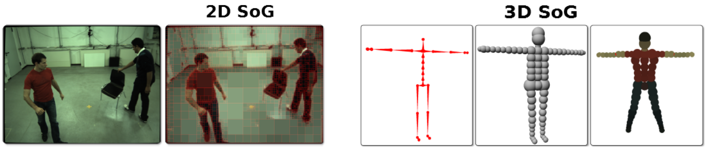
Body Motion Capture Problem



Method Overview (C. Stoll, N. Hasler, J. Gall, H. Seidel, C. Theobalt *"Fast Articulated Motion Tracking using a Sums of Gaussians Body Model" (ICCV) 2011*)



SoG-based Image domain and Body model



- B_i : Gaussian kernel
  - 3D case : 3D sphere
  - 2D case : 2D superpixel

$$\boxed{K(x) = \sum_{i=1}^{n} B_i(x)}$$

color model $C = \{c_i\}_i$

2D-2D SoG Similarity

- how to compare two SoG images?
- two SoG images K_a, K_b, associated color models C_a, C_b
- similarity

overlapping of Gaussians + image similarity

$$E(K_a, K_b, C_a, C_b) = \int_\Omega \sum_{i \in K_a} \sum_{j \in K_b} d(\mathbf{c}_i, \mathbf{c}_j) B_i(x) B_j(x) d\mathbf{x}$$

$d(\mathbf{c}_i, \mathbf{c}_j)$ similarity measure between color models

Objective function

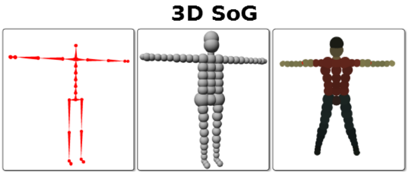
- goal : estimate pose-parameters Θ(position, angle joints) of kinematic skeleton from input images $\mathbf{I}$
- given
  - n_{cam} cameras C_l with SoG images (K_l, C_l)
  - 3D body model (K_m, C_m) parametrized by Θ
- similarity function

$$E(\Theta) = \frac{1}{n_{cam}} \sum_{l=1}^{n_{cam}} \frac{1}{E(K_l, K_l)} E(K_l, \Psi_l(K_m(\Theta)), C_l, C_m)$$

- objective function

$$\mathcal{E}(\Theta) = E(\Theta) - w_l E_{lim}(\Theta) - w_a E_{acc}(\Theta)$$

Actor specified body model estimation



- manually initialize pose parameters Θ + estimate(refinement) of Θ
- optimize shape parameters Θ_{shape} that define bone lengths, position, variance of each blob
- calculate Gaussian blob mean color $\mathbf{c}_i$

Articulated Motion Tracking

- estimate current pose parameters
  - given estimated pose of the model in the previous frames

$$\Theta_0^t = \Theta^{t-1} + \alpha(\Theta^{t-1} - \Theta^{t-2})$$

- optimizes parameters :
  maximize objective function

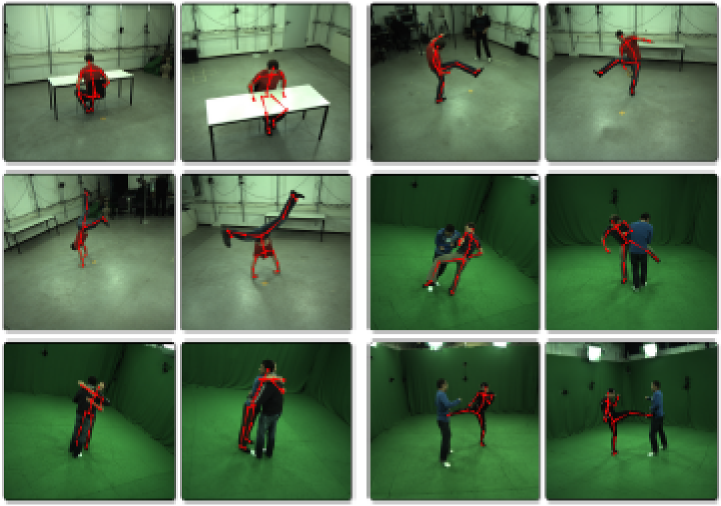
$$\mathcal{E}(\Theta) = E(\Theta) - w_l E_{lim}(\Theta) - w_a E_{acc}(\Theta)$$

- conditioned gradient ascent

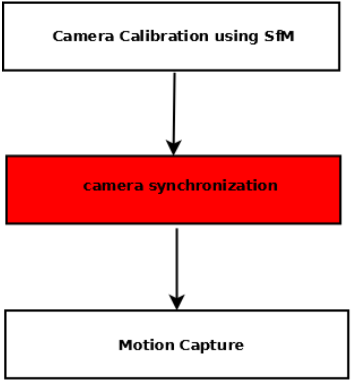
$$\Theta_{i+1}^t = \Theta_i^t + \nabla E(\Theta_i^t) \circ \sigma_i$$

$$\sigma_{i+1}^{(l)} = \begin{cases} \sigma_i^{(l)} \mu^+, & \text{if } \nabla E(\Theta_{i-1}^t) > 0 \\ \sigma_i^{(l)} \mu^-, & \text{if } \nabla E(\Theta_{i-1}^t) \leq 0 \end{cases}$$

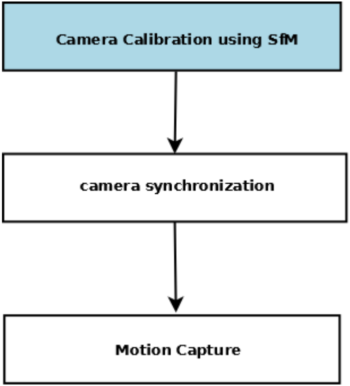
Results



Method Overview (Hasler et al. *"Markerless Motion Capture with Unsynchronized Moving Cameras"(CVPR) 2009*)



"Using Unsynchronized Moving Cameras"



Single Camera Structure-from-Motion

- find corresponding feature points in consecutive frames(KLT-Tracker,SIFT-matching)
- filter out moving feature points, $p_{j,k}$(RANSAC with multi-view constraints)
- estimate 3×4 camera matrix A_k parameters
- determine 3D object point $\mathbf{P}_j$
- Bundle adjustment :

$$\arg \min_{A_k, \mathbf{P}_j} \sum_{j=1}^{J} \sum_{k=1}^{K} d(p_{j,k}, A_k \mathbf{P}_j)^2$$

Multi-Camera Structure-from-Motion

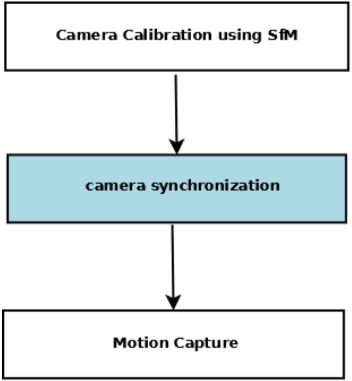
- SfM for each camera
  - N camera matrices reconstructions $A_{k,n}$, 3D object points $\mathbf{P}_{j,n}$
- register N reconstructions into a global coordinate system
  - estimate transformation H between independent reconstructions
  - find and merge tracked in at least two cameras common 3D object points

$$\arg\min_{A,\mathbf{P}} = \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{k=1}^{K} d(\mathbf{p}_{j,k,n}, A_{k,n}\mathbf{P}_{j,n})^2$$

3D Background Reconstruction

- estimate geometry of the static background of the scene
- reconstruction of a surface from a sparse set of point cloud $\mathbf{P}_{j,n}$
- remove outliers that do not form surfaces(tensor voting filter)
- smooth out the remaining noise(bilateral moving least squares filtering)
- triangle mesh reconstruction

"Using Unsynchronized Moving Cameras"



Synchronizing Audio Signals

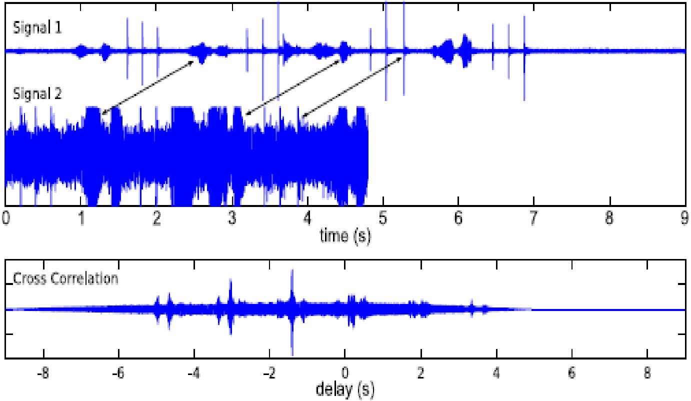
- at least one sound source in the scene
- α_i : audio signal captured by the i-th camera
- cross correlation between the audio signal of cameras i,j :

$$\alpha_i \star \alpha_j \equiv \overline{\alpha}_i(-t) * \alpha_j(t)$$

- efficient computation of cross correlation using Fast Fourier Transform(FFT)

Synchronizing Audio Signals

- requirement : the observed scene is small
- audio delay between signals : peak of the cross correlation signal



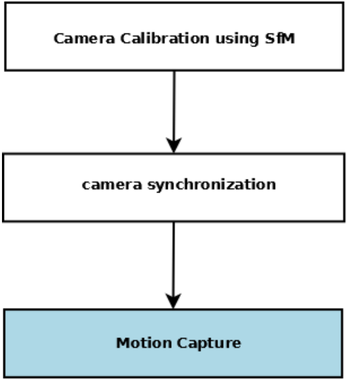
Correction for Large Camera Displacements

- camera position c_i known from the calibration step
- known position of the sound source $\mathbf{s}$
- delay between audio signals of camera i,j

$$d_{ij} = \Delta_{ij} + \frac{1}{c}(d(c_j - \mathbf{s}) - d((c_j - \mathbf{s}))$$

- N cameras, N-1 unknown Δ_i(temporal shift of every camera)
- N(N-1)/2 equations(N-1 linearly independent)
- extend to unknown source

"Using Unsynchronized Moving Cameras"



Kinematic Chains

- respective movement of a point X_i

$$X_i' = exp(\theta\xi)(exp(\theta_1\xi_1)\dots exp(\theta_n\xi_n))X_i$$

- pose configuration (6+n)-D vector
  $\chi = (\hat{\xi}, \theta_1, \dots, \theta_n) = (\hat{\xi}, \Theta)$
- task : compute vector χ from calibrated and synchronized data

Silhouette Extraction

- image segmentation(level set function $\Phi \in \Omega \to \Re$)
- minimize energy

$$E(\Phi, p_1, p_2, \chi) = \lambda \int_\Omega (\Phi - \Phi_0(\chi))^2 dx -$$

$$\int_\Omega H(\Phi) log p_1 + (1 - H(\Phi)) log p_2 + \mathbf{v}|\nabla H(\Phi)| dx$$

- output : segmentation of the images

Pose Estimation

- given image points on the contour line to reconstruct 3D projection rays
- projection ray : 3D plucker line $L_i = (n_i, m_i)$ (3D unit direction n_i, 3D moment m_i)
- error function for each point-line pair

$$X_i'(\hat{\xi}, \Theta) \times n_i - m_i = 0$$

- linearisation of equation
- iteration to optimize all correspondences simultaneously

Results

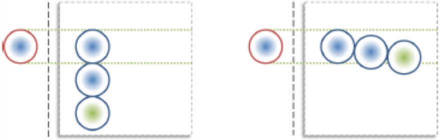
Conclusions

- two methods on markerless human motion capture presented
- novelties
  - represent 3D body model, image domain as a Sum of Gaussians
  - exploit audio signal for camera synchronization
- initialization phase $\rightarrow$ actor-specified 3D body model
- online tracking, 2D SoG images computation, estimate parameters of kinematic model
- camera calibration, background reconstruction,
- camera synchronization, pose parameter estimation

Discussion

- object wear tight clothes
- two actors with the same clothes
- online tracking should start from one of the four "initialization" poses
- cannot faithfully model highly textured regions
- difficult to accurately track twisting motions
- cameras number greater or equal to 5
- outdoor scenes

3D-2D SoG Similarity



$$E(K_{\mathbf{I}}, \Psi(K_m), C_{\mathbf{I}}, C_m) = \sum_{i \in K_{\mathbf{I}}} min\Big(\Big(\sum_{j \in \Psi(K_m)} E_{ij}\Big), E_{ii}\Big)$$

- $K_{\mathbf{I}}$: image model
- $\Psi(K_m)$: projected SoG model

Discussion

- large audio delays $\rightarrow$ inaccurate tracking
- fast movement $\rightarrow$ necessary prediction of subject's motion
- sound source distinctness
- more than one actors

Future Work

- real-time human motion capture
- usage of cheap, low-quality user cameras
- minimize required cameras number
- flexible number of interacting actors in scene
- face motion analysis


THANK YOU