Real-time Full-Body Motion Capture from Video and IMUs Charles Malleson, Marco Volino, Andrew Gilbert, Matthew Trumble, John Collomosse and Adrian Hilton

Overview

A real-time full-body motion capture system is presented which uses input from a sparse set of inertial measurement units (IMUs) along with images from two or more standard video cameras and requires no optical markers or specialized infra-red cameras. A real-time optimization framework incorporates constraints from the IMUs, cameras and a prior pose model. The combination of video and IMU data allows the full 6-DOF motion to be recovered including axial rotation of limbs and drift-free global position. Tests on indoor and outdoor captured data show the effectiveness of the approach for tracking a wide range of human motion in real time.

Cost function

robust kinematic pose estimates for each frame.

PriorData $E_R(\boldsymbol{\theta}) + E_P(\boldsymbol{\theta}) + E_A(\boldsymbol{\theta})$ $E_{PP}(\boldsymbol{\theta}) + E_{PD}(\boldsymbol{\theta})$ $E(\boldsymbol{\theta})$ Solved pose — $E_{pp}(\boldsymbol{\theta})$ Ori. meas $E_{PD}(\boldsymbol{\theta})$ Projected pose PCA subspace PCA prior projection term **Orientation term** Encourages the pose to lie close to Minimizes the difference between the a reduced dimensionality subspace solved and measured orientation of the of prior observed poses (soft joint body segment type enforcement) **2D Position term** PCA prior deviation term Minimizes the distance between the Discourages deviation beyond the prior observed range of motion projected solved joint locations and the 2D detections from the image (soft joint limit) 2D pos. meas. Pos. (*t* - 1) Pos. (t - 2)Proj. pos. target Acceleration term Acc. target -Minimizes the difference between the solved and measured acceleration at the IMU site Acc. meas. UNIVERSITY OF

Signal Processing

CVSSP, University of Surrey, Guildford, U.K.

Motivation

- Applications in entertainment (film, TV, games, VR, AR), life sciences • Real-time full-3D kinematic motion capture with low encumbrance, flexible capture configurations
- Overcoming limitations of previous methods

| Features / Approach | | IMU [13] | Kinect | Andrews 2016 [6] | SID [18] | CPM [19] | Vnect [12] | Trumble 2017[16] | Ours |
|---|--------------|--------------|--------------|---------------------|--------------|--------------|--------------|---------------------|--------------|
| Realtime, online (video rates) | \checkmark | \checkmark | V | ∠010 [0] √ | | | | ∠01/ 10 √ | \checkmark |
| Outputs full 6DOF motion (incl. axial rotation) | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | | \checkmark | | \checkmark |
| Outputs unambiguous 3D global position | \checkmark | | \checkmark | \checkmark | | | | | \checkmark |
| Kinematic skeleton for animation | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | | \checkmark | | \checkmark |
| Dynamic lighting and background | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | | \checkmark |
| Outdoor | | \checkmark | | | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark |
| Robust to heavy occlusion | | \checkmark | | \checkmark | \checkmark | | | | \checkmark |
| Long range (> 5m) | \checkmark | \checkmark | | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark |
| Marker-less | | \checkmark | \checkmark | | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark |
| Subject fully unencumbered | | | \checkmark | | | \checkmark | \checkmark | | |

The solver combines input from IMUs (orientation and acceleration) and video (2D joint detections) with a pose prior to produce accurate and



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Flexible input configuration

The method can trade accuracy against capture hardware and setup complexity (number of cameras and IMUs) as well as framerate. In the experiments, IMU input was from Xsens MTWs [13], while 2D joint detections are obtained from a stateof-the art convolutional pose machine (CPM) detector [19].

Frame packing for increased detection throughput

The 2D joint detection is a bottleneck requiring > 150 ms per image on our order to maintain video rate while detecting on multiple camera views, we pack regions of interest from several input images into a single image for detection and resolve the results to their originating frame and camera.

Number of cameras Between 2 and 8 cameras were used (multiple cameras constrain depth)





Positional subsampling To increase the output framerate, 2D detection may be performed on a subset of input frames



Results



Outdoor capture

A an outdoor dataset Outdoor 1 was captured with cameras in a 120 degree arc along with 12 IMUs.





Large, uncontrolled capture area

References

[4] Vicon Blade. http://www.vicon.com [6] S. Andrews, I. Huerta, T. Komura, L. Sigal. and K. Mitchell Real-time Physic based Motion Capture with Sparse Sensors. CVMP2016 [13] D. Roetenberg, H. Luinge, and P. Slycke. Xsens MVN: Full 6DOF Human Motion Tracking Using Miniature Inertial Sensors. Technical report, pages 1–7, 2013 [16] M. Trumble, A. Gilbert, C. Malleson, A. Hilton, and J. Collomosse. Total Capture: 3D Human Pose Estimation Fusing Video and Inertial Sensors. BMVC 2017

Machines. CVPR 2016 data capture.



Packed ROI image for CPM detection (from frames *B* and *C*)

Comparison of configurations

Quantitative evaluation on the *Total Capture* dataset [16] using A full set of 13 IMUs or a sparse set of 6 IMUs with HQ ('high quality', 8 cam, detection on all frames) and HS ('high speed', 4 cam, detection on 2/8 frames).

| | S1 | S2 | S2 | S3 | S3 | S4 | S5 | S5 | | |
|------------------|------|------|------|------|------|------|------|------|------|--|
| | FS3 | FS1 | RM3 | FS1 | FS3 | FS3 | A3 | FS1 | Mean | |
| Pos. error (cm) | | | | | | | | | | |
| Ours, 13 IMU, HQ | 7.4 | 5.3 | 3.9 | 6.7 | 6.7 | 6.4 | 6.4 | 7.0 | 6.2 | |
| Trumble [16] | 9.4 | 16.7 | 9.3 | 13.6 | 8.6 | 11.6 | 14.0 | 10.5 | 11.7 | |
| Ours, 13 IMU, HS | 8.5 | 5.4 | 3.8 | 7.4 | 7.3 | 7.7 | 6.6 | 7.5 | 6.8 | |
| Ours, 6 IMU, HQ | 9.8 | 7.1 | 6.6 | 10.0 | 10.7 | 9.2 | 9.0 | 10.0 | 9.1 | |
| Ours, 6 IMU, HS | 14.3 | 9.4 | 10.8 | 19.4 | 17.1 | 13.9 | 13.3 | 16.5 | 14.3 | |
| Ori. error (deg) | | | | | | | | | | |
| Ours, 13 IMU, HQ | 11.2 | 5.1 | 5.0 | 8.3 | 9.3 | 8.0 | 7.6 | 8.2 | 7.8 | |
| Ours, 13 IMU, HS | 11.2 | 5.1 | 5.0 | 8.3 | 9.3 | 8.0 | 7.6 | 8.2 | 7.8 | |
| Ours, 6 IMU, HQ | 16.3 | 9.2 | 8.7 | 13.2 | 15.7 | 13.0 | 11.8 | 12.1 | 12.5 | |
| Ours, 6 IMU, HS | 18.3 | 10.9 | 10.6 | 16.2 | 19.7 | 14.8 | 14.3 | 15.1 | 15.0 | |
| | | | | | | | | | | |



[18] T. von Marcard, B. Rosenhahn, M. Black, and G. Pons-Moll. Sparse Inertial Poser: Automatic 3D Human Pose Estimation from Sparse IMUs. Eurographics 2017 [19] S.-E. Wei, V. Ramakrishna, T. Kanade, and Y. Sheikh. Convolutional Pose

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