An optimization-based approach to human body motion capture using inertial sensors

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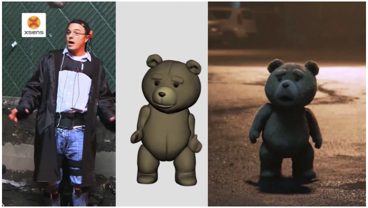
Applications of inertial motion capture



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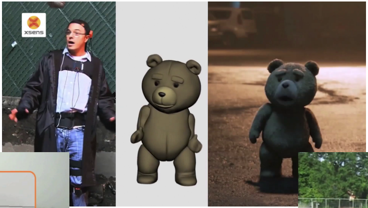

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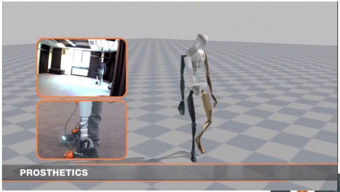

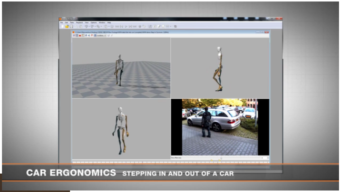

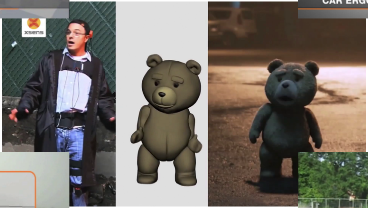

Inertial motion capture

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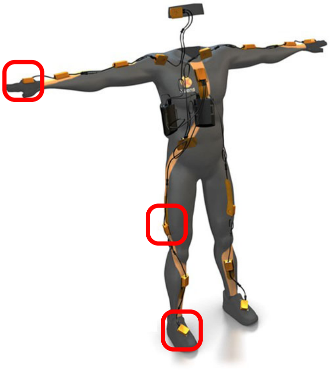
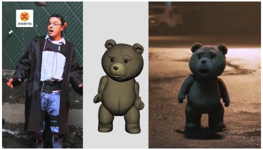
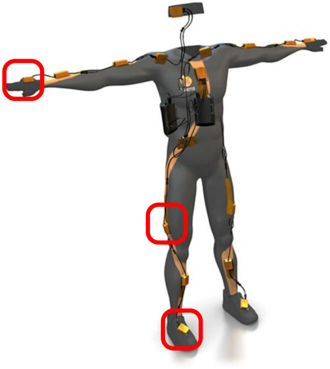


17 sensors placed on the body

Estimate the relative position and orientation of body segments.





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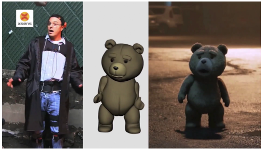
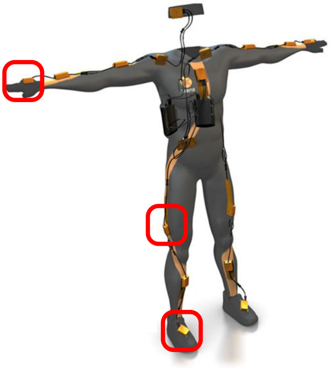
Estimate the relative position and orientation of body segments.

Possibly also estimate the body's absolute position.





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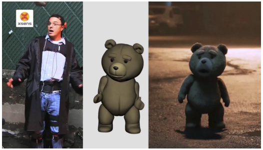

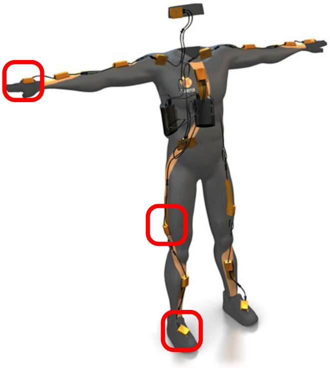

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Inertial measurement units

- Accelerometers
- Gyroscopes
- Magnetometers

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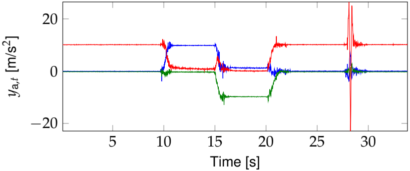
Accelerometer measures:

- Sensor's acceleration
  $\Rightarrow$ Change in position
- Direction of gravity
  $\Rightarrow$ Inclination



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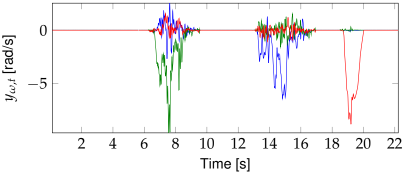
Gyroscope measures:

- Sensor's angular velocity
  $\Rightarrow$ Change in orientation



Inertial measurement units

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Magnetometer measures:

- The local magnetic field
  $\Rightarrow$ Heading (provided that magnetic field is not disturbed)

- Accelerometers
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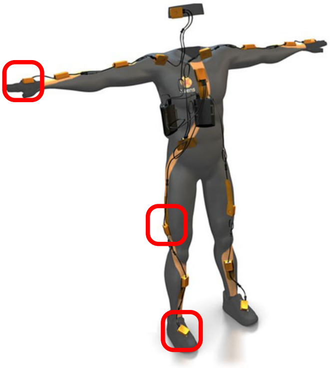
$\left.\begin{array}{l}\text{Accelerometers}\\\text{Gyroscopes}\end{array}\right\}$ Inertial sensors

Inertial sensors and magnetometers are often used for orientation estimation. They also provide information about the change in position.

Sensor fusion

Sensor fusion



- Accelerometers
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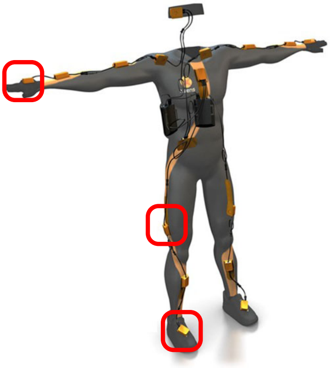
$\left.\begin{matrix}\text{Accelerometers}\\ \text{Gyroscopes}\end{matrix}\right\}$ Inertial sensors

The magnetic field at the different sensor locations is typically different.

Sensor fusion



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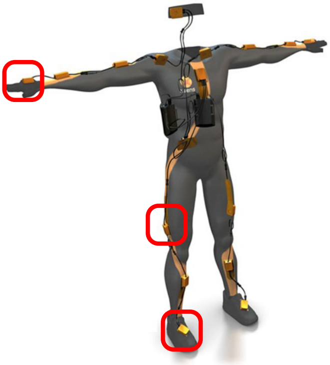

- Accelerometers
- Gyroscopes

} Inertial sensors

- Magnetometers

\+ Biomechanical model

Assuming that the body segments are connected to each other, the *relative* position and orientation of the body is observable (if the subject is not standing completely still).

We solve the motion capture problem by solving a *maximum a posteriori* (MAP) problem

$$\min_{z=\{x_{1:N},\theta\}} \underbrace{-\log p(x_1 \mid y_1) - \log p(\theta)}_{\text{initial state + prior}}$$

$$\underbrace{-\sum_{t=2}^{N} \log p(x_t \mid x_{t-1}, \theta)}_{\text{dynamic model}} \underbrace{-\sum_{t=1}^{N} \log p(y_t \mid x_t, \theta)}_{\text{biomechanical/sensor model}}$$

$$\text{s.t.} \quad \underbrace{c_{\text{bio}}(z) = 0}_{\text{biomechanical model}}$$

Problem formulation

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$x_{1:N}$: time-varying states such as the sensor positions, velocities and orientations, the body segment positions and orientations.
θ: constant model parameters such as sensor biases.
$y_{1:N}$: inertial measurements.

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$c_{\text{bio}}(z)$: constraints imposed by the biomechanical model.

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$$
\begin{aligned}
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$\Rightarrow$ A constrained nonlinear weighted least-squares problem.

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Solve this as a batch problem using standard solvers.

Biomechanical model - strategy

The body segments are connected at the joints.

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⇒ constraint

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$\Rightarrow$ constraint

The position and orientation of the sensors on the body is approximately constant.

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⇒ objective function

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$\Rightarrow$ objective function

Some joints are restricted in their rotational freedom (optional).

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Experimental setup

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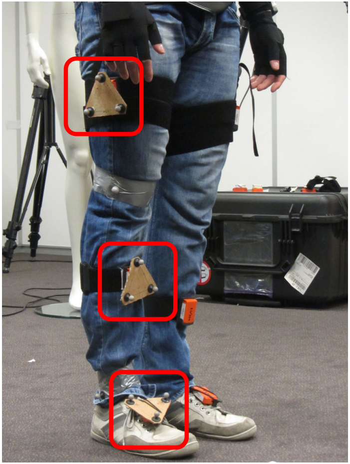
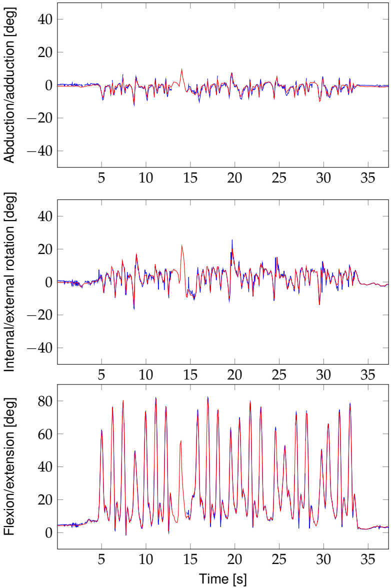


Markers for an optical reference system

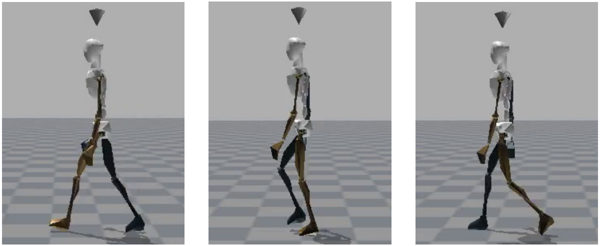
Knee joint angle estimates



Angle between the sensors on the upper and lower leg while walking.

Blue: Optical reference
Red: Estimates from our algorithm

Results using our algorithm.



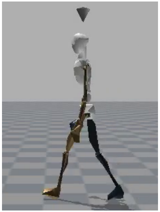
Body pose estimates

Show movie

Conclusions

- We estimate the body's relative position and orientation using inertial sensors placed on multiple body segments.
- We obtain the estimates by solving a constrained optimization problem, where we make use of a biomechanical model.
- Our algorithm is shown to result in accurate joint angle estimates as compared to an optical reference system.



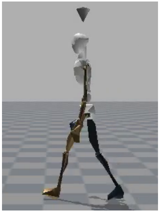


More information:

- The extended abstract for the conference.
- Manon Kok, Jeroen Hol and Thomas Schön, **An optimization-based approach to human body motion capture using inertial sensors.** *Proceedings of the 19th World Congress of the International Federation of Automatic Control*, 2014.

http://users.isy.liu.se/en/rt/manko/





Thank you for your attention!

Questions?

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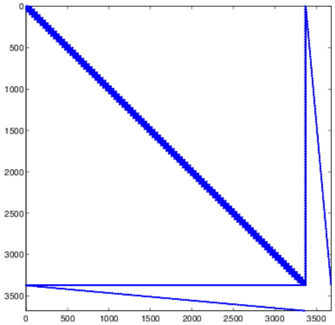
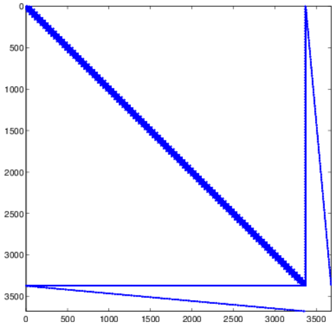


Only 0.56% of the matrix-elements are non-zero.

Solving the problem for an experiment of 10 seconds takes:

- about 5 minutes on an AMD X4 2.8 GHz processor (first inefficient Matlab implementation).
- Initial tests with a C-implementation show that speed improvements of up to 500 times are easily obtained.
- A moving horizon implementation would further speed up the computations.

Computation time



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$z \in \mathbb{R}^{(9N_S+6N_B+3)N+3N_S}$

equality constraints: $3N$

Example:

7 body segments, 7 sensors,

10s, 10Hz

$\Rightarrow$

$\sim$ 11000 variables

300 constraints

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