ISTITUTO
DI TECNOLOGIE DELLA
COMUNICAZIONE,
DELL'INFORMAZIONE
E DELLA
PERCEZIONE

Scuola Superiore
Sant'Anna

A novel approach to motion tracking with wearable sensors based on Probabilistic Graphical Models

Emanuele Ruffaldi
Lorenzo Peppoloni
Alessandro Filippeschi
Carlo Alberto Avizzano

2014 IEEE International Conference on Robotics and Automation (ICRA) Hong Kong Convention and Exhibition Center
Hong Kong, China.

Outline

- Research Context
- Motivations
- Existing Approaches
- Proposed Solution
- Evaluation
- Results

Research Context

Motion analysis, expertise modeling and synthesis for…

Sport training in Real and Virtual Environments with focus on rowing

Complex articulated motion (26 DOF)
100Hz loop embedded for feedback and VR

Motion and force tracking for ecological ergonomic assessment

Motion Capture Techniques

Different types of MoCap systems

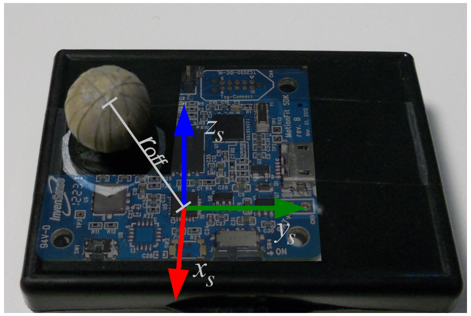
- Vision
  - Marker Based
    - Passive
    - Active
  - Markerless
    - Multi-view
    - Depth
- IMU
- Mechanical
- Electromagnetical

Wearable MoCaP

Inertial sensors embedded in suit

- Gyroscopes
- Accelerometers
- Magnetometers

+	−
Real-time recording	No global position
High accuracy	Drifts
Self-contained	
Portability	
No occlusion	
Low cost	



Objectives

- Modeling Objectives
  - Multiple Body Links
  - Flexibility in Modeling
    - Supporting changes in configuration such as sensor position
- Computing Objectives
  - Real-time Reconstruction
  - Scalability

Bayesian Filters for Inertial Reconstruction

Linear model

- KF [Zhu2004]

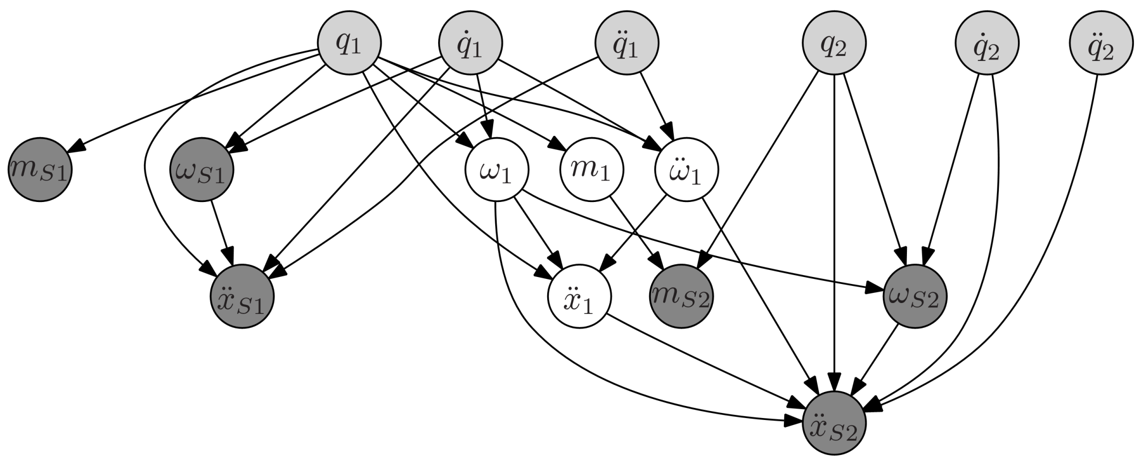
Non-linear model

- EKF [Cheng2007]
- UKF [El-Gohary 2012]
- PF [Zhang 2011]

- Each of the variables involved in the models is potentially correlated to all the others
- Losing control of the covariance matrices makes impossible to directly represent variables independence

Proposed Approach: PGM

- More flexibility in variables representation
- Variable independencies are directly represented, this leads to more realistic assumptions
- Already successfully exploited for human motion analysis [Ganapathi2010] [Cheng2013]



ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

Proposal

In this work we propose:

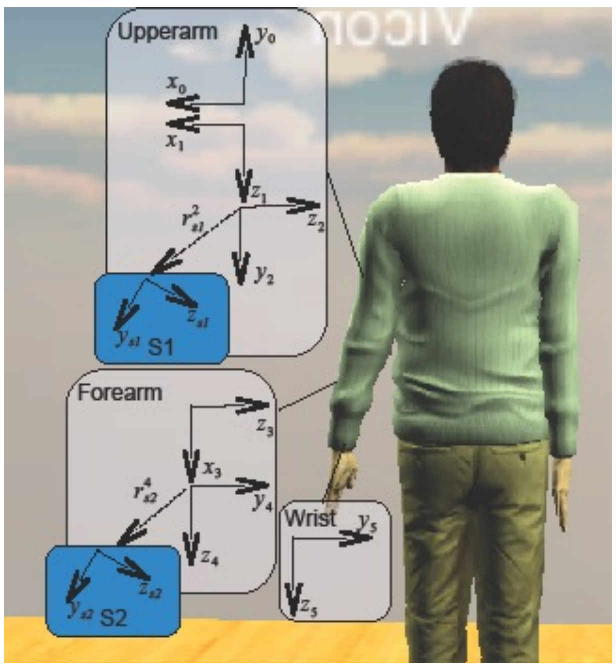
- A novel approach to motion reconstruction based on PGM, adopting a PGM framework particularly suitable for exploiting IMUs sensors measurements
- We show an example of how to apply PGM to human motion reconstruction. In particular:
  1. We present two PGMs for reconstructing body pose and motion based on IMUs signals
  2. We evaluate the models against an optical tracking system and state of the art Kalman Filters based models

Body Kinematics

The chosen Kinematic representation is based on Denavit-Hartenberg that, in comparison to quaternion approaches:

- Automatic enforcement of axial constraints of joints
- Extraction of joint variables for force modeling

The model discussed is 5DOF, more complex models are possible (e.g. 7DOF with clavicle in Peppoloni 2013)



Frame	a_i	α_i	d_i	ϑ_i
1	0	$\pi/2$	0	ϑ_1
2	0	$\pi/2$	0	$\vartheta_2 - \pi/2$
3	l_{ua}	0	0	$\vartheta_3 + \pi/2$
4	0	$\pi/2$	0	$\vartheta_4 + \pi/2$
5	0	0	l_{fa}	ϑ_5

Kinematic Model

State Model

$$\dot{x}_i = A_i x_i + \nu$$

$$A_i = \begin{bmatrix} 1 & T_s & \frac{1}{2}T_s^2 \\ 0 & 1 & T_s \\ 0 & 0 & 1 \end{bmatrix}$$

$$x_i = [q_i, \dot{q}_i, \ddot{q}_i]^T \qquad i = 1, 2, \ldots, n$$

Random Walk
[El-Gohary 2011 and Peppoloni 2013]

Measurement Model

$$z = h(x) + \epsilon$$

Every joint measurements vector can be written as a function of all the previous joints state of the kinematic chain

$$\begin{aligned} z_{S1} &= h_1(x_{13}) \\ z_{S2} &= h_2(x_{15}) \end{aligned}$$

$$x_{ab} = [x_a^T \ldots x_b^T]^T$$

UKF Complexity

- Definition
  - s sensors
  - f frames
  - n state variables
  - m observations
- Linear Prediction: $4n^3$
- Cholesky: $n^3/6$
- Sigma Points: $2n+1$
- Measurement Function: $250 (s + f)$
  - s sensors
  - f frames
- Kalman Correction: $m^3+2m^{2n}+28mn^2+8n^3$
- Overall (s,f,n,m)
  - $20n^3 + (52m)n^2 + (2m^2 + 500f + 500s)n + m^3 + 250f + 250s$

ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

PGM Representation

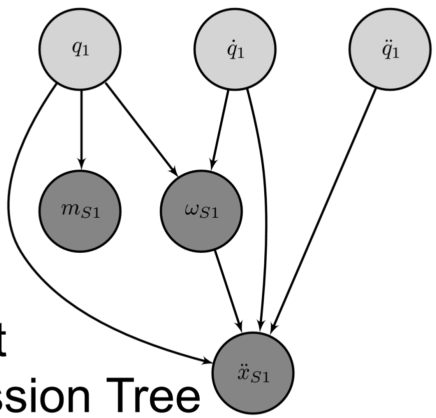
One DoF – One sensor DAG representation

m_{s1} : Earth Magnetic Field

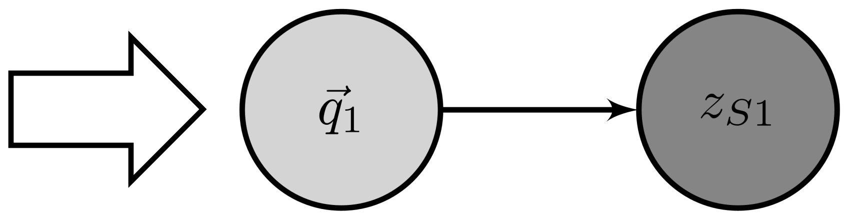
$\ddot{x}_{s1}$: Linear Acceleration

ω_{s1} : Angular Velocity

$$
\begin{aligned}
\omega_i &= R_p^i(\omega_p + \dot{q}_{p+1} z_0) \\
\dot{\omega}_i &= R_p^i(\dot{\omega}_p - \dot{q}_{p+1} S(z_0)\omega_p + \ddot{q}_{p+1} z_0) \\
\ddot{x}_i &= R_p^i \ddot{x}_p - S(r_{p,i}^i)\dot{\omega}_i + S(\omega_i)^2 r_{p,i}^i + g_i \\
g_i &= R_p^i g_p \\
m_i &= R_p^i m_p
\end{aligned}
$$



Explicit
Expression Tree

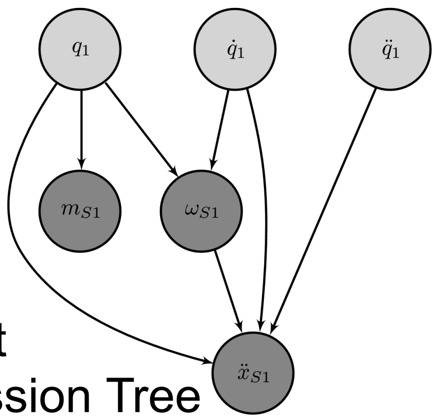


PGM Representation

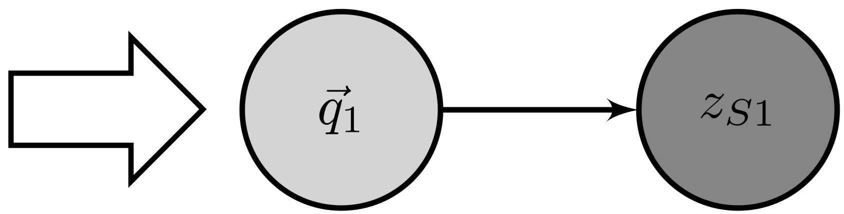
One DoF – One sensor DAG representation

$$
\begin{aligned}
m_{s1} &: \quad \text{Earth Magnetic Field} \\
\ddot{x}_{s1} &: \quad \text{Linear Acceleration} \\
\omega_{s1} &: \quad \text{Angular Velocity}
\end{aligned}
$$

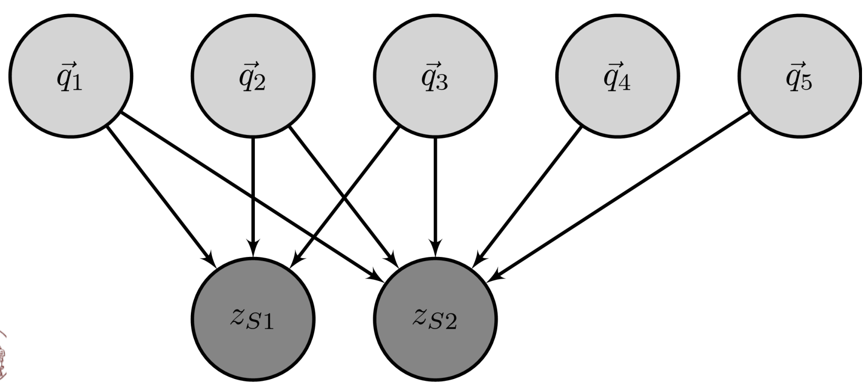
$$
\begin{aligned}
\omega_i &= R_p^i(\omega_p + \dot{q}_{p+1} z_0) \\
\dot{\omega}_i &= R_p^i(\dot{\omega}_p - \dot{q}_{p+1} S(z_0)\omega_p + \ddot{q}_{p+1} z_0) \\
\ddot{x}_i &= R_p^i \ddot{x}_p - S(r_{p,i}^i)\dot{\omega}_i + S(\omega_i)^2 r_{p,i}^i + g_i \\
g_i &= R_p^i g_p \\
m_i &= R_p^i m_p
\end{aligned}
$$



Explicit
Expression Tree



Five DoF – Two sensors DAG representation



PGM Adoption

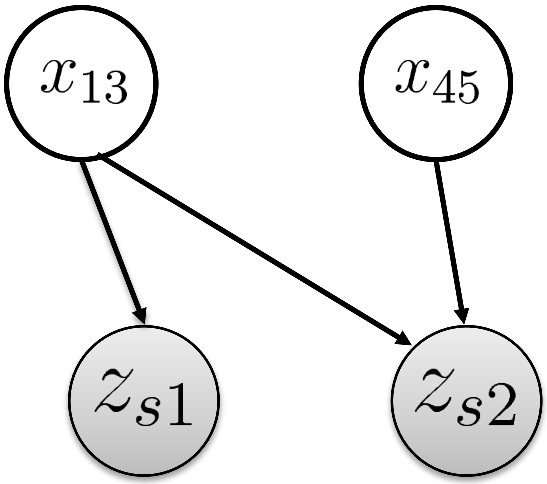
- It is well known that an Expression Tree of Linear dependent equations with Gaussian distributions is equivalent to a single Matrix sparse problem
- Non-linearity in the Equations makes the propagation of belief using Sigma points non-trivial

- We propose a decomposition of the tree that **exploits the kinematic structure** allowing:
  - Reduction of computational cost
  - Flexibility in the structure
  - (Future) adoption of priors in the D-H parameters

Message Passing: Algorithm

- Propagation of Belief involving Sigma Points decomposition
- Exemplified using the two blocks of the 5DOF structure above
- Two approaches discussed and evaluated:
  - Single propagation S1S2
  - Iterated propagation S1S2S1
- Operations expressed in terms of Canonical of Normal form of the Gaussian

Different from Cascade Kalman filtering



Composed states

Message Passing: Operations

Operations involved in the approach, classical steps from UKF

TempUpdate

State

$$x_{i_k}^{-} = A x_{i_{k-1}} + \nu$$

Covariance

$$\Sigma_{x_{i_k}}^{-} = A \Sigma_{x_{i_{k-1}}} A^T + R.$$

UT Transform

$$\mathcal{Y}_i = h(\chi_i) \quad i = 0, \ldots, 2n$$

$$\bar{y} = \sum_{i=0}^{2n} \omega_i^{(m)} \mathcal{Y}_i$$

$$P_y = \sum_{i=0}^{2n} \omega_i^{(c)} \left(\mathcal{Y}_i - \bar{y}\right)\left(\mathcal{Y}_i - \bar{y}\right)^T$$

$$P_{xy} = \sum_{i=0}^{2n} \omega_i^{(c)} \left(\chi_i - \bar{x}\right)\left(\mathcal{Y}_i - \bar{y}\right)^T$$

Message Passing: Operations

UT Update

Evidence is pushed towards *x*

$$y_x = y_x^- + Y_x^- Y_{xz}^- Q^{-1} (\hat{z} - z^- + Y_{xz}^T y_x^-)$$
$$Y_x = Y_x^- Y_{xz} Q^{-1} Y_{xz}^T Y_x^-$$

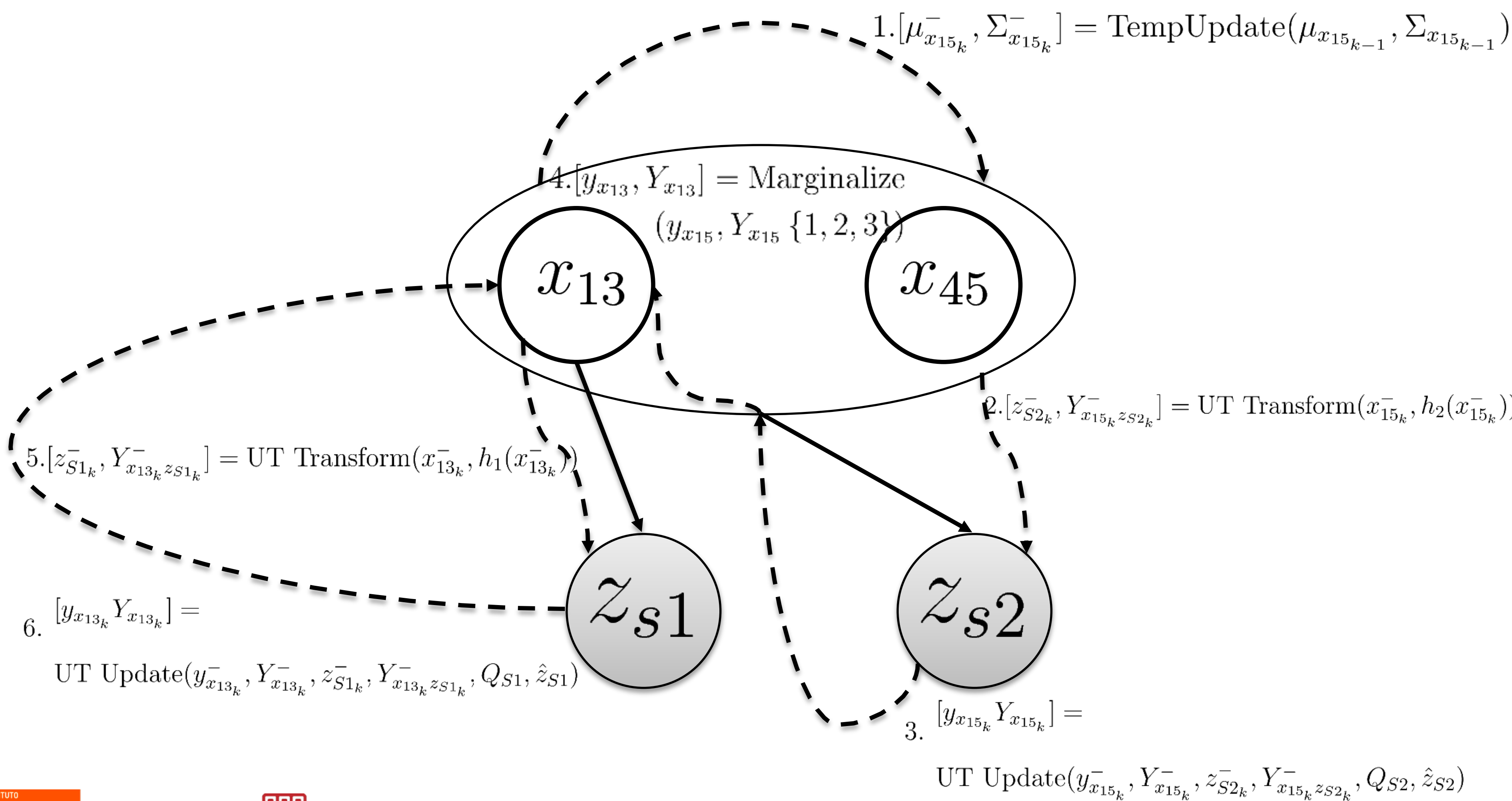
Marginalize

$$\tilde{Y} = Y(s,s) - Y(s,s) Y(t,t)^{-1} Y(s,t)$$
$$\tilde{y} = y(s) - Y(s,t) Y(t,t)^{-1} y(t)$$

Where *s* is the set of indices to keep in the marginalization and *t* the remaining ones to be marginalized out

Message Passing: Algorithm

S2S1 Algorithm



ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

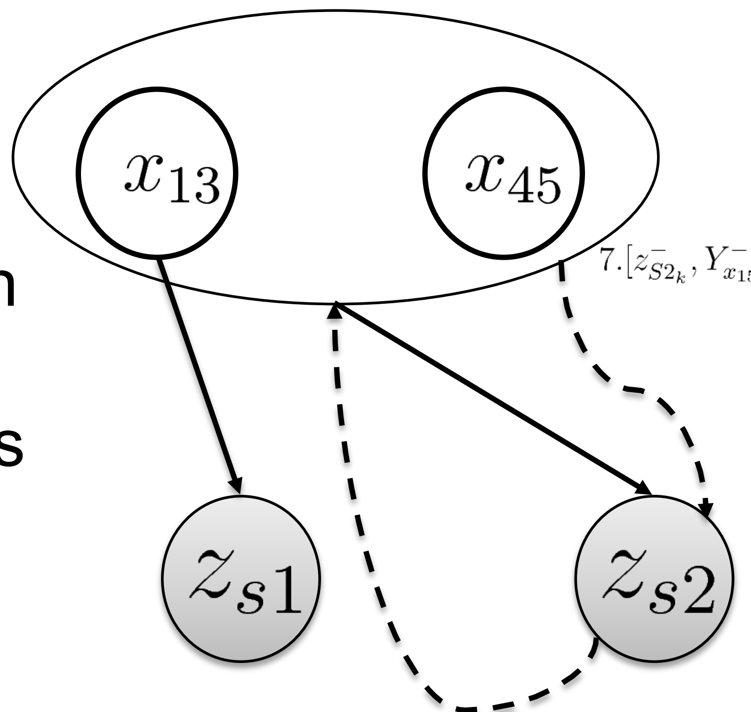
Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

Message Passing: Algorithms

S2S1S2 Algorithm

This two steps can be repeated with S1 and S2, but it is not guaranteed to converge to a better estimation



$7.[z^-_{S2_k}, Y^-_{x15_k z_{S2_k}}] = \text{UT Transform}(x_{15_k}, h_2(x_{15_k}))$

8. $[y_{x15_k} Y_{x15_k}] =$

$\text{UT Update}(y_{x15_k}, Y_{x15_k}, z^-_{S2_k}, Y^-_{x15_k z_{S2_k}}, Q_{S2}, \hat{z}_{S2})$

Validation

Two validation steps:

1. Synthetic joints angles and measurements

$$
\begin{aligned}
q_1(t) &= \cos(\gamma t)^2 + \sin(2\gamma t)^2 \\
q_4(t) &= \cos(\gamma t)^2 + \cos(2\gamma t)^2 \\
q_2(t) &= \cos(\gamma t) \\
q_3(t) &= 0 \\
q_5(t) &= -\sin(\gamma t)
\end{aligned}
$$

2. Real measures obtained from a healthy male volunteer wearing two Bluetooth Invensense MPU9150 IMUs (upper arm and fore arm).

Results: Synthetic Data

Averaged RMS of the joint variables in the 5 DoF kinematic chain and comparison between S2S1, S2S1S2 and UKF

	S2S1	S2S1S2	UKF
$q\ [rad]$	0.034	0.029	0.029
$\dot{q}\ [rad/sec]$	0.084	0.077	0.078
$\ddot{q}\ [rad/sec^2]$	1.0782	0.9832	1.0243

ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

Results: Experimental Setup

- Results are compared against Vicon optical motion capture system
- Six reflective markers allowed to reconstruct upper limbs kinematic.
- The subject performs a sequence of functional movements involving all arm DoF

Results: Real Data

Comparisons between optical estimation and S2S1, S2S1 and UKF algorithms

RMS

	S2S1	S2S1S2	UKF
q_1 $[deg]$	6.68	6.78	6.84
q_2 $[deg]$	7.67	6.64	7.58
q_3 $[deg]$	3.81	3.77	3.80
q_4 $[deg]$	7.25	7.24	7.29
q_5 $[deg]$	15.47	15.49	15.50

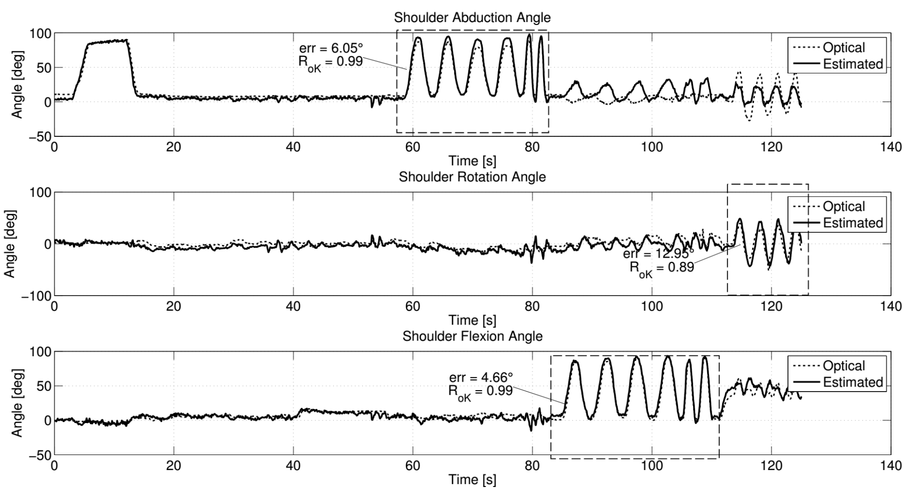
Correlation coefficient

	S2S1	S2S1S2	UKF
q_1	0.94	0.94	0.93
q_2	0.81	0.81	0.80
q_3	0.98	0.98	0.98
q_4	0.98	0.98	0.98
q_5	0.75	0.74	0.74

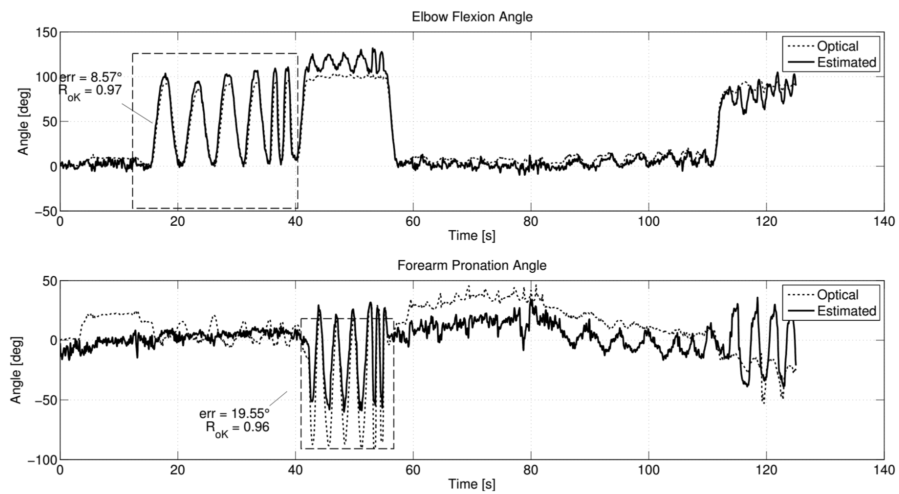
Results: Real Data

Motion tracking results obtained with the S2S1S2 algorithm. The DoF-related functional movements are highlighted by the boxes.

Shoulder



Elbow



ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

Results

- Synthetic measures:
  - The iterated message passing algorithm performs as the UKF with a slight improvement in $\ddot{q}$ estimation.
  - The basic message passing algorithm performs instead slightly worse than the UKF.
- Real data:
  - The message passing algorithm performs as the UKF
  - The iterated message passing algorithm performs slightly better with an increment of accuracy of 1° on the shoulder rotation estimate.

Conclusions

- We presented a novel approach to human motion reconstruction with IMUs that exploits PGMs.
- The model represents better the actual dependencies of the variables compared to Kalman Filters.
- We proposed a message passing algorithm and an iterated message passing algorithm to estimate joints variables
- The results of the two algorithms have been compared to the UKF showing a slight improvement in the estimation using the iterated message passing algorithm

Further Developments

1. Refining the message passing algorithm to maintain also the independence among different joints variables and increase the accuracy of estimates
2. Evaluation of computational cost, to make the algorithm suitable for real-time embedded motion tracking
3. Implementation using Information Matrix and Squared Root representation for improved precision

Data and values of covariances used will be published for comparative testing.

Thanks for the attention

email:
e.ruffaldi@sssup.it

ISTITUTO DI TECNOLOGIE DELLA COMUNICAZIONE, DELL'INFORMAZIONE E DELLA PERCEZIONE

Scuola Superiore Sant'Anna

PERCRO Perceptual Robotics Laboratory

References

[1] R. Zhu and Z. Zhou. A real-time articulated human motion tracking using tri-axis inertial/magnetic sensors package. Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 12(2):295–302, 2004

[2] Y. Cheng and M. D. Shuster. Robustness and accuracy of the quest algorithm. Advances in the Astronautical Sciences, 127:41–61, 2007.

[3] M. El-Gohary and J. McNames. Shoulder and elbow joint angle tracking with inertial sensors. Biomedical Engineering, IEEE Transactions on, 59(9):2635–2641, 2012

[4] Z. Q. Zhang and J. K. Wu. A novel hierarchical information fusion method for three-dimensional upper limb motion estimation. Instrumentation and Measurement, IEEE Transactions on, 60(11):3709– 3719, 2011

[5] V. Ganapathi, C. Plagemann, D. Koller, and S. Thrun. Real time motion capture using a single time-of-flight camera. In Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, pages 755–762. IEEE, 2010.

[6] C. A. Cheng, T. H. Huang, and H. P. Huang. Bayesian human intention estimator for exoskeleton system. In Advanced Intelligent Mechatronics (AIM), 2013 IEEE/ASME International Conference on, pages 465–470. IEEE, 2013