Learning Odometry on Small Humanoid Robot and Application to Robocup Football Game

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Definition

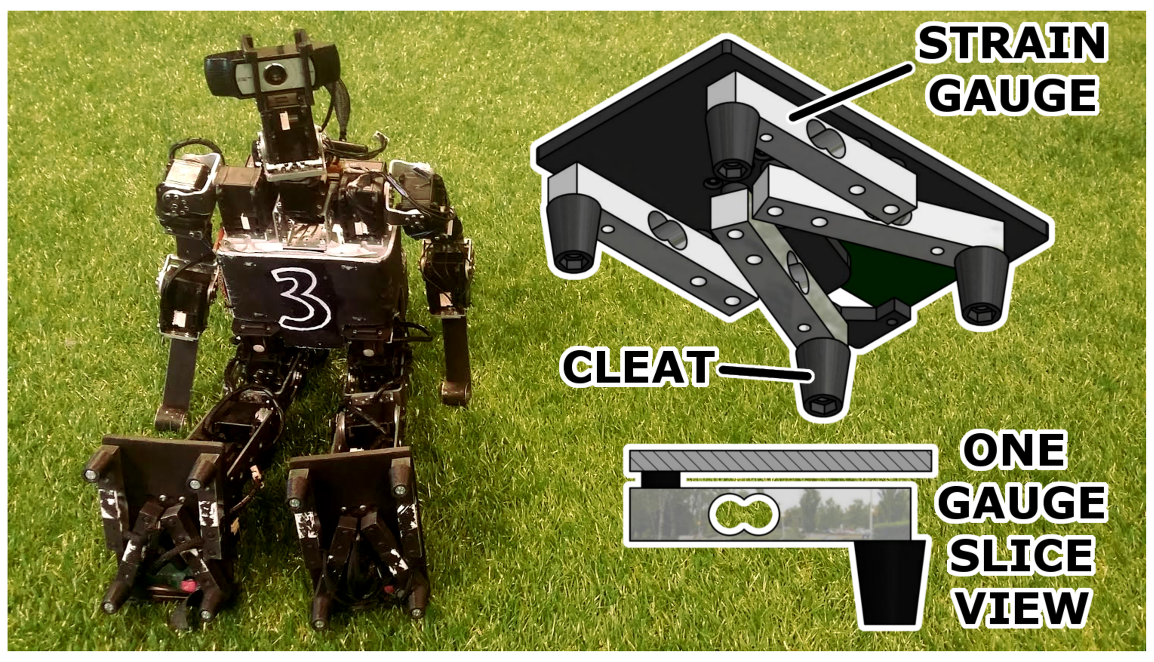
Odometry (dead reckoning): *estimating the position by integrating displacements over time.* Displacements can be estimated:

– from sensors (motor encoder, IMU, vision, ...)
– from future controls (simulation)

Abstract

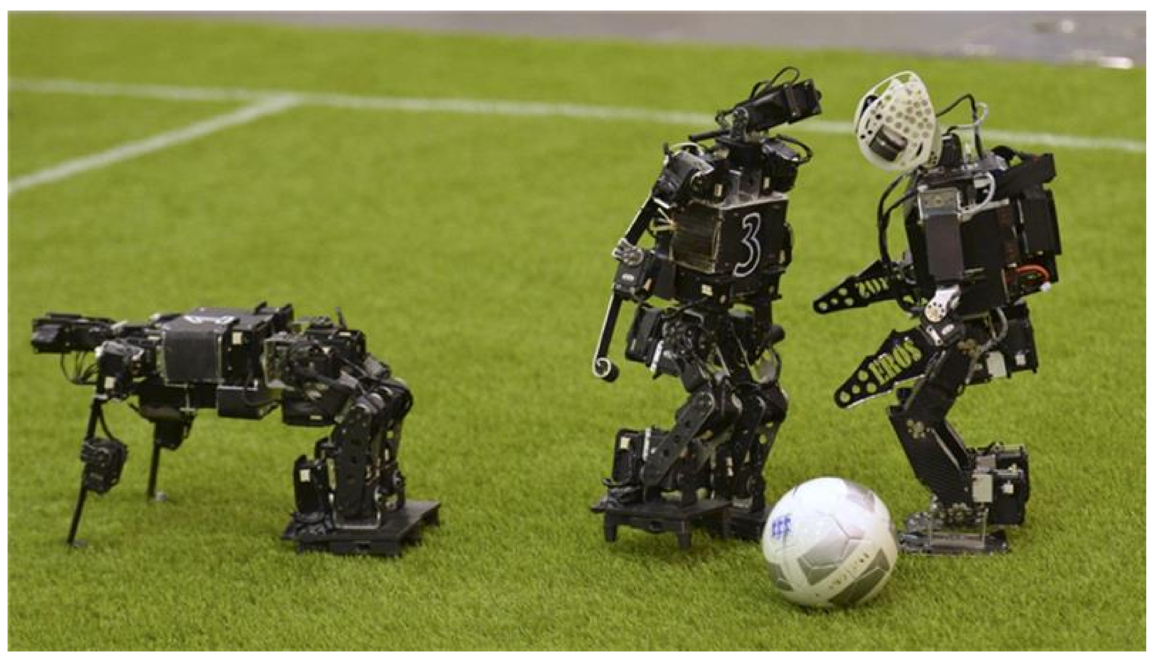
– uses no vision (only internal sensors)
– is real time (≈10ms)
– improves accuracy using machine learning
– compares 4 odometry methods
– compares 2 ground surfaces (carpet, grass) and 2 walk engines (open, closed loop)
– will improve absolute localization on football field during Robocup competition

Sigmaban Humanoid Platform



Humanoid Robot. 20 degrees of freedom (6 per leg, 3 per arm, 2 on the head) Dynamixel servomotors. Position encoders, webcam, IMU (accelerometers, gyroscopes), foot pressure sensors. Small 1.6GHz embedded processor. 54cm height, weights 3.8Kg. Learning experiments are easier on small robots than tall ones.

Robots are Playing Football



The Robocup: annual international robotics competition (3000 participants). Humanoid Soccer, Wheeled Soccer, Rescue, Home, . . .

Why football is an interesting and difficult challenge for robots ?

– Benchmark for state of the art algorithms
– Mechanics, electronics, software robustness
– Real time vision in complex conditions
– Locomotion and motor control speed, adaptability and stability
– Navigation and path planning
– Adversarial game in partially observable noised environment
– Small and low cost robots have inaccurate mechanics, controls and models but are still deterministic

The *Rhoban Football Club* won the third place in Humanoid KidSize Soccer League at Robocup 2015 in China.

Good odometry estimate ⇒ accurate robot's localization on field

Learning Footsteps with LWPR Regression

Footsteps: robot's head displacements (forward x, lateral y, rotation θ) between two support foot swap.

2 classic odometry estimations:

– **Method 1: simulation based odometry:** integration of forward kinematics motion fed only with motor reference positions (no sensor)
– **Method 2: sensors based odometry:** integration of forward kinematics motion fed with measured motor encoders, IMU and foot pressure (selecting support foot)

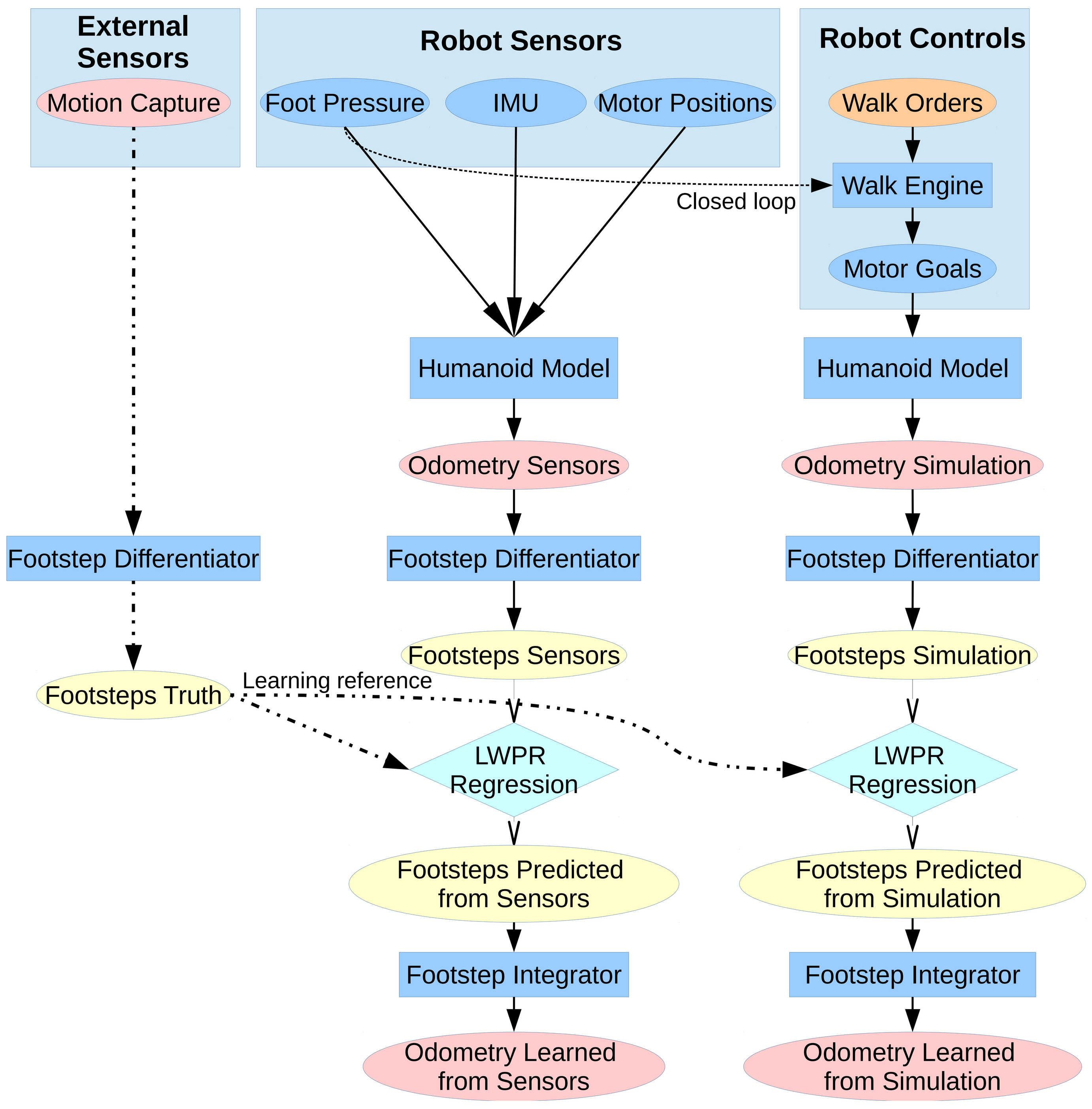
2 learning odometry estimations:

– **Method 3: learned from simulation odometry:** ground truth footstep displacements are predicted from simulation based footsteps
– **Method 4: learned from sensors odometry:** ground truth footstep displacements are predicted from sensors based footsteps

Sensors based regression models: 3x($\mathbb{R}^9 \longrightarrow \mathbb{R}^1$)

Simulation based regression models: 3x($\mathbb{R}^7 \longrightarrow \mathbb{R}^1$)

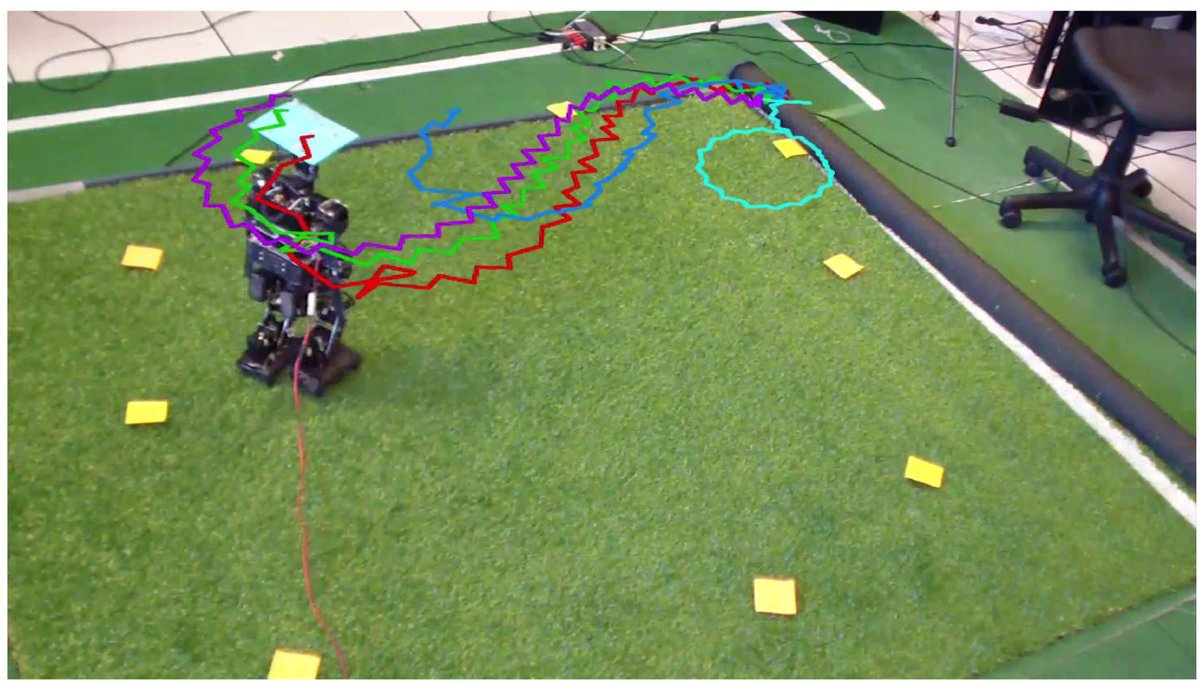
Learning uses LWPR non linear non parametric regression.

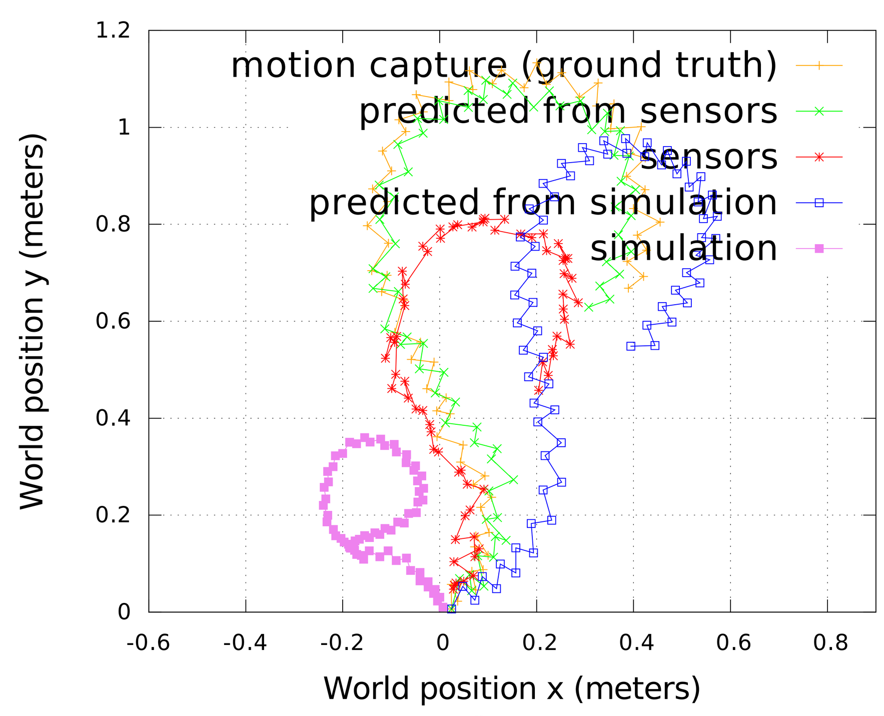


$$\left\{\begin{array}{l}\Delta(x,y,\theta)_{t,\ sensor\ based}\\ \Delta(x,y,\theta)_{t-1,\ sensor\ based}\\ support\_foot_{\ t,\ sensor\ based}\\ step\_duration_{\ t,\ sensor\ based}\\ step\_duration_{\ t-1,\ sensor\ based}\end{array}\right. \longmapsto \Delta x_{truth}$$

$$\left\{\begin{array}{l}\Delta(x,y,\theta)_{t,\ simulation\ based}\\ \Delta(x,y,\theta)_{t-1,\ simulation\ based}\\ support\_foot_{\ t,\ simulation\ based}\end{array}\right. \longmapsto \Delta x_{truth}$$

Experimental Comparisons and Results



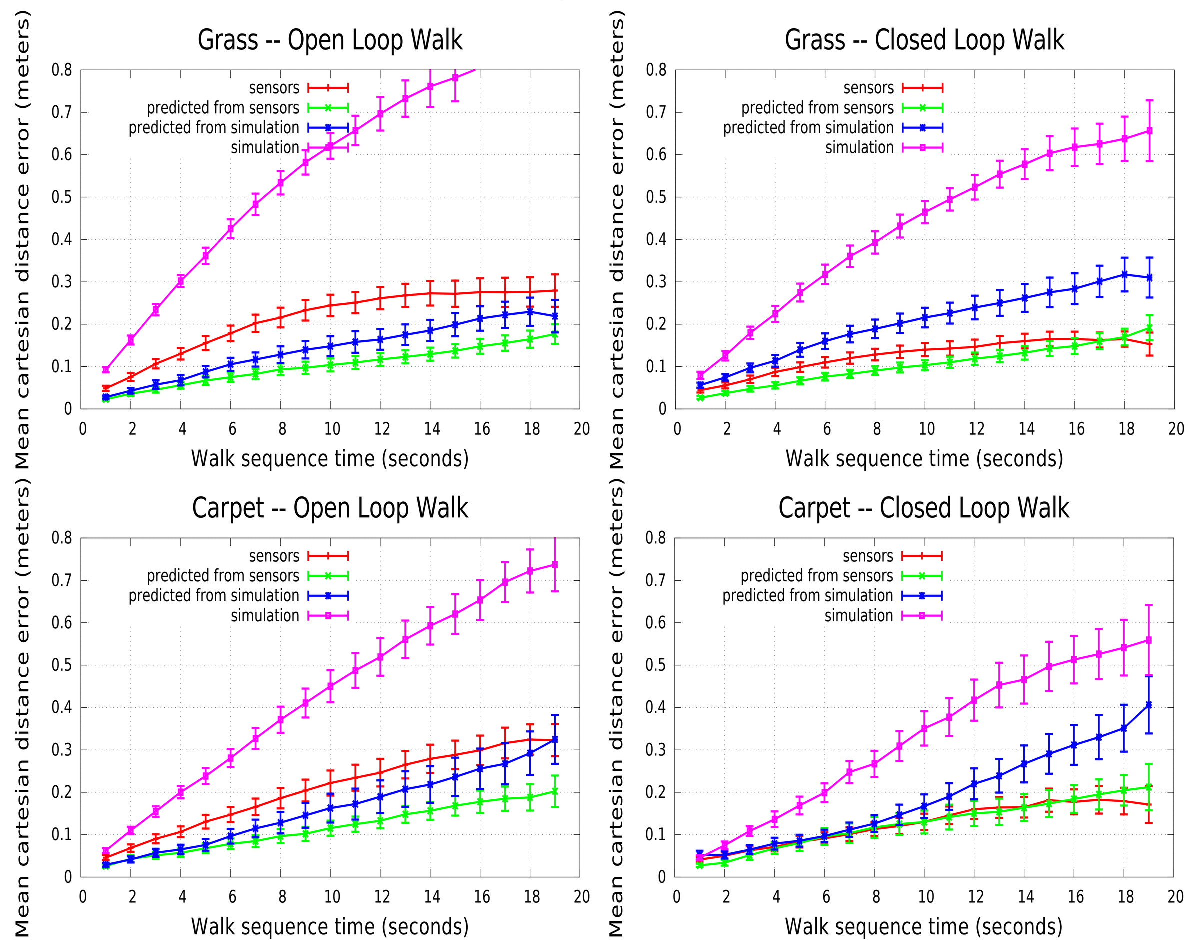


– Learning convergence: about 2-3 minutes of walk exploration
– Test on 60 walk sequences of 20 seconds

⇒ On artificial grass and using an open loop walk, average drift error improvements using learning:
sensors based: 24.5cm → 10.3cm
simulation based: 62.0cm → 14.8cm

Comparison: soft artificial grass *vs.* thin carpet, fully open *vs.* simple closed loop walk engine.

– Carpet → artificial grass ⇒ more motion noise
– Open loop → Simple closed loop ⇒ walk stabilization
– Closed loop walk ⇒ no good prediction without sensor



Conclusion and Beyond

– Learning improves both off-line simulation and online sensors based odometry.
– Off-line odometry will improve planning
– Real time online odometry will improve localisation

⇒ Odometry is an essential basis for planning and navigation.

References

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