

CZECH TECHNICAL UNIVERSITY IN PRAGUE FACULTY OF ELECTRICAL ENGINEERING CENTRE FOR MACHINE PERCEPTION



NIFTi – Natural Human-Robot Cooperation in Dynamic Environments

2010 – 2014 EC project FP7-ICT-247870 NIFTi Michal Reinštein



Natural Human-Robot Cooperation in Dynamic Environments

SEARCH AND RESCUE ROBOTICS



FUKUSHIMA 2010 UGV: iRobot Packbot, Warrior, Talon, Bobcat, Dragon runner UAV: Honeywell T-Hawk



iROBOT Warrior

http://www.irobot.com/gi/ground/710_Warrior/



NREC Dragon Runner

http://www.rec.ri.cmu.edu/projects/dragonrunner/

NIFTI – PROJECT COOPERATION

Benif.#	Beneficiary name	Benef.	Country
	53	short name	12
1.	Deutsches Forschungszentrum für	DFKI	Germany
(crd.)	Künstliche Intelligenz GmbH		
2.	Netherlands Organization for Ap-	TNO	The Netherlands
	plied Scientific Research		
3.	Fraunhofer Institut Intelligente	Fraunhofer	Germany
	Analyse- und Informationssysteme		,
4.	BlueBotics SA	BLUE	Switzerland
5.	Eidgenossische Technische	ETHZ	Switzerland
	Hochschule Zürich		
6.	Czech Technical University Prague	CTU	Czech Republic
7.	'Sapienza' University of Roma	ROMA	Italy
8.	Institut für Feuerwehr und Rettung-	FDDo	Germany
	stechnologie FDDo		
9.	Corpo Nazionale Vigili del Fuoco	VVFF	Italy

NIFTI – PROJECT AIMS



Developing a novel rover platform to meet the demands of operating in dynamic environments
 Minimizing task load for human and optimizing workflow
 Integration – bringing human factor into cognitive rescue robots
 Situation awareness – conceptual understanding of environment
 Flexible planning w.r.t. dynamic changes in environment
 User adaptive human-robot communication
 Multiple humans & robots cooperation
 Continuous evaluation with end user organizations
 Realistic missions in real-life training areas

NIFTI PLATFORM – HARDWARE



Embeded PC: Kontron KTGM45/mITX Plus
 Embeded CPU: Kontron CPU KTGM45-CPU_Q9100
 2D laser scanner: : SICK LMS-151
 Omnicam: Point Grey Ladybug 3
 IMU/GPS: X-sens MTI-G
 ASUS Xtion Pro
 Thermocam Micro-Epsilon TIM160

NIFTI PLATFORM – SOFTWARE

UBUNTU 12.4 (64 bit) C++ / Python

WILLOW GARAGE PRODUCTS
ROS – Robot Operating System
OpenCV
PCL

OpenCV



FROM DATA TO UNDERSTANDING



METRIC MAPPING



 Rotating laser in front of the robot
 Range data assembled into point clouds Fast ICP algorithm http://ros.org/wiki/ethzasl_icp_mapping
 Density subsampling (memory)
 Results in 3D metric map for SLAM
 No loop closure yet
 Gap detection
 Traversability analysis

METRIC MAPPING



TOPOLOGICAL MAPPING



 Incremental segmentation
 Segmentation into discrete regions
 Voronoi diagram
 Identification of changes in metric map & recomputation
 Graph-based structure over (centroids of) regions
 Required for different levels of planning

TOPOLOGICAL MAPPING



OBJECT DETECTION & LOCALIZATION - CARS





Robust 2D & 3D object detection
Using omni-directional camera
Associating detection with laser
Filtering out false positives
False positives negatively impact situation wareness, human-robot interaction
Visual features to 3D data

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OBJECT DETECTION & LOCALIZATION - CARS



OBJECT DETECTION & LOCALIZATION - VICTIMS



FUNCTIONAL MAPPING

OCU – OPERATION CONTROL UNIT



INTEGRATED INTELLIGENCE



USAR MISSION – MIRANDOLA, IT 2012



May 20 – June 18, 2012, Mirandola, Italy 246 seismic activities of magnitudes 3 – 6.1 Radius of 50 km, 900 000 people affected Red area: San Francesco church



USAR MISSION – MIRANDOLA, ITALY 2012

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CZECH TECHNICAL UNIVERSITY IN PRAGUE FACULTY OF ELECTRICAL ENGINEERING CENTRE FOR MACHINE PERCEPTION



NIFTi Inertial Navigation System

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Michal Reinštein



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INERTIAL SENSORS

LOW-COST INS

Time correlated degradation in precision due to sensor errors



SOLUTION:

- Aiding : odometry, visual odometry, laser range data, ultrasound, GPS / GLONAS, magnetometer
- Sensor Error Calibration & Estimation (KF, EKF, UKF)



INERTIAL NAVIGATION SYSTEM

Double integration of accelerations to obtain position
 Integration of angular rates to obtain angle of direction of the accelerometers' sensing axes
 Transformation from body frame b to navigation frame n
 Compensation: gravity, Earth rate, Coriolis force, centripetal acceleration, systematic & stochastic sensor errors



DATA FUSION



SENSOR SELECTION





The frequency response of the sensor should be compatible with the system state-spectrum.

The sensor noise spectrum should be separable from the system state-spectrum.

MOTION DYNAMICS

To sense motion dynamics sensor errors have to be compensated

LONG TERM ERRORS (drift) SHORT TERM ERRORS (integration of vibration)

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 f_{c}

Error reduction due to estimation using KF and correction feedback

Error reduction due pre-filtering

MOTION DYNAMICS

LONG TERM ERRORS

SHORT TERM ERRORS

f_s / 2

SENSOR DRIFT

Result of manufacturing imperfections of the sensors

 Systematic component (bias) quantified by calibration (can be compensated)
 Stochastic component approximated by random process (can be modelled and estimated)

No correlation to the input

 Refers to the rate at which the error accumulates with time



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IEEE Std 528-2001: Standard for Inertial Sensor Terminology

Projection of sensor bias, scale factor and non-linearity to the sensor conversion characteristics – CALIBRATION required



DATA FUSION – ERROR MODELS













NOISE MODEL EQUATIONS

Noise Type	Autocorrelation Function ψ_x Power Spectral Density Ψ_x	State-Space Form	ulation And Model	
White noise	$\psi_x(\tau) = \sigma^2 \delta^2(\tau)$	Always treated as n	neasurement noise	
	$\Psi_x(\omega) = \sigma^2$			
Random walk	$\psi_x(\tau) = (undefined)$	$\dot{x} = w(t)$	$x_k = x_{k-1} + w_{k-1}$	
	$\Psi_x(\omega) \approx \sigma^2 / \omega^2$	$\sigma_x^2(0)=0$	$\sigma_x^2(0) = 0$	
Random	$\psi_x(\tau) = \sigma^2$	$\dot{x} = 0$	$x_k = x_{k-1}$	
constant	$\Psi_{x}(\omega) = 2\pi\sigma^{2}(\omega)$	$\sigma_x^2(0) = \sigma^2$	$\sigma_x^2(0) = \sigma^2$	
Harmonic	$\psi_x(\tau) = \sigma^2 \cos(\omega_0 \tau)$	$\dot{\mathbf{x}} = \begin{bmatrix} 0 & 1 \end{bmatrix}_{\mathbf{x}}$	$P(0) = \begin{bmatrix} \sigma^2 & 0 \end{bmatrix}$	
	$\Psi_{x}(\omega) = \pi \sigma^{2} \delta(\omega - \omega_{0})$	$\begin{bmatrix} -\omega_0^2 & 0 \end{bmatrix}^n$		
	$+\pi\sigma^2\delta(\omega+\omega_0)$			
Exponentially	$\psi_x(\tau) = \sigma^2 e^{-\alpha \tau }$	$\dot{x} = -\alpha x + \sigma \sqrt{2\alpha} w(t)$	$x_k = e^{-\alpha} x_{k-1}$	
correlated	$\Psi(\alpha) = \frac{2\sigma^{\alpha}\alpha}{2\sigma^{\alpha}\alpha}$	$\sigma_x^2(0) = \sigma^2$	$+\sigma\sqrt{1-e^{-2\alpha}}w_{k-1}$	
	$\omega^2 + \alpha^2$		$\sigma_x^2(0) = \sigma^2$	
p th order GM	$(-)$ $(-)^{2-\alpha_{p} z } \sum_{n=1}^{p-1} (p-1)^{2}$	$\left(2\alpha_{p}\left \tau\right \right)^{p-n-1}\left(p+n+1\right)$!	
protess	$\psi_x(\tau) = \sigma^2 e^{-p \tau} \sum_{n=0}^{\infty} \frac{1}{(2\pi)^n}$	(2p-2)!n!(p-n-1)!	-	
TableShaping Filter Equations with σ Being Standard Deviation, δ Kronecker Delta,				
$1/\alpha$ Correlation Time, P Covariance Matrix And k Discrete Time Step				

DATA FUSION – PRE-FILTERING



WAVELET TRANSFORMATION

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \Psi\left(\frac{t-b}{a}\right) dt$$

$$x(n) = \sum_{j} \sum_{k} C_{j,k} \Psi_{j,k}(n)$$

ANALYSED SIGNAL x(t)

WAVELET SHIFTING ... b

WAVELET SCALING ... a



CWT(a, b) = CORRELATION COEFFICIENT

WMRA DATA DE-NOISING

THE PRINCIPLE OF WMRA:

- Procedure of successive signal decomposition
- Scaling (LP) & wavelet (HP) filters & down-sampling 2
- MATLAB: wden(signal, wavelet, LOD, threshold)



WAVELET TRANSFORMATION



Accelerometer Output Data De-noising (Lateral Axis) for Level of De-noising 3 and 7



Accelerometer Output Data De-noising (Vertical Axis) for Level of De-noising 3 and 7







VICON EXPERIMENTS



Vicon Room at ASL, ETH, Zurich

VICON EXPERIMENTS



LEICA GEOSYSTEMS EXPERIMENTS





3DOF position data at 5-10 Hz
Automatic target tracking
Delay 200ms
Range 3.5 km
Precision approx. 1-3mm





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NIFTi Complementary Filtering

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INFLUENCE OF DRIFT & VIBRATION



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COMPLEMENTARY FILTERING



COMPLEMENTARY FILTERING



COMPLEMENTARY FILTERING



COMPLEMENTARY FILTER DESIGN



Frequency characteristics of the transfer functions for the combination of attitude angles obtained using coarse alignment (low-pass) and integration of angular rates (high-pass)

RESULTS – NIFTI PITCH



Pitch angle estimated during UGV field-testing on ramps of given slope: pitch angle estimated using complementary filtering (blue), standard pitch angle output using MTi-G Xsens (red)

RESULTS – NIFTI ROLL



Roll angle estimated during UGV field-testing on ramps of given slope: roll angle estimated using complementary filtering (blue), standard roll angle output using MTi-G Xsens (red).

RESULTS – NIFTI YAW



Yaw angle estimated during UGV field-testing on ramps of given slope: yaw angle estimated using proposed complementary filtering (blue), standard yaw angle output using MTi-G Xsens (red).