Multisensory Integration Network for Mobile Robot Self-motion Estimation

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Introduction and Problem Statement

Spatial cognition is important for both natural and artificial organisms to adapt their motor responses in a specific goal-directed context [1]. **Perceiving ego-motion** is an essential component of such spatial perception. This poster focuses on **heading estimation** as a **component of ego-motion**; a process that requires **fusion of different sensory signals** to obtain a **robust** and **unambiguous** description of an agent's current orientation within its environment.

Current **engineered technical systems** (such as autonomous mobile robots) typically use **compute-intense algorithms** for sensor fusion, [2], which hardly work in real-time; yet their results in complex unprepared environments are typically inferior to human performance.

Here we employ a **distributed computation process** with a **learning/adaptation** mechanism to maintain congruence of fused cues (i.e. minimize interference and conflicts). We model such information processing as **distributed graphical network**, in which independent neural computing nodes obtain and represent sensory information, while **processing and exchanging exclusively local data** (similar to Cortical information processing). Given various external sensory stimuli, the **network relaxes** to a **globally consistent estimate of the robot's heading angle**, similar to the scenario in [3].

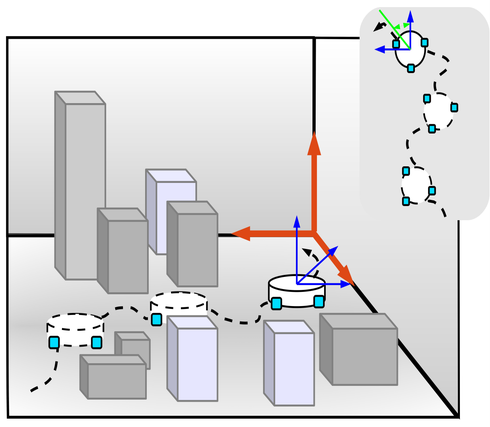

Fig.1. Typical scenario of robot exploration

Test Setup and Comparison with State-of-the-art Methods

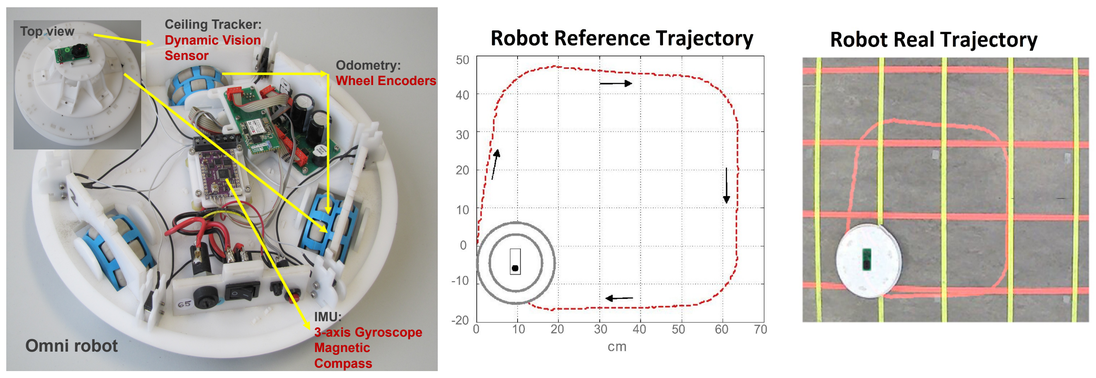

Fig.2. Left: Test setup for the 4 dimensional sensor fusion network: omnidirectional mobile robot. Right: robot reference and real trajectory in top-down view

Criteria	State-of-the-art approaches (Bayesian)	Proposed model
Complexity Computational Costs	large number of probabilities to apply probabilistic inference [2].	compute multiple simple update rules (eq.1).
Flexibility Possibility to add further sensory modalities	requires parameters adjustments for additional sensory modalities; adding sensors improves performance but increases complexity [3].	sensor addition (adding more Update rules/constraints) is straightforward and without complexity increase.
Robustness Handling sensor failures, conflicts, and uncertainty	dedicated means to detect failures, not generally applicable; challenges in assigning probabilities in an uncertain context [2].	abnormal sensor activity can be detected and penalized by adapting η (e.g. the influence of that sensor in the global estimate).

Table 1. Comparison between state-of-the-art and the proposed model for sensor fusion

Network Architecture and Experimental Results

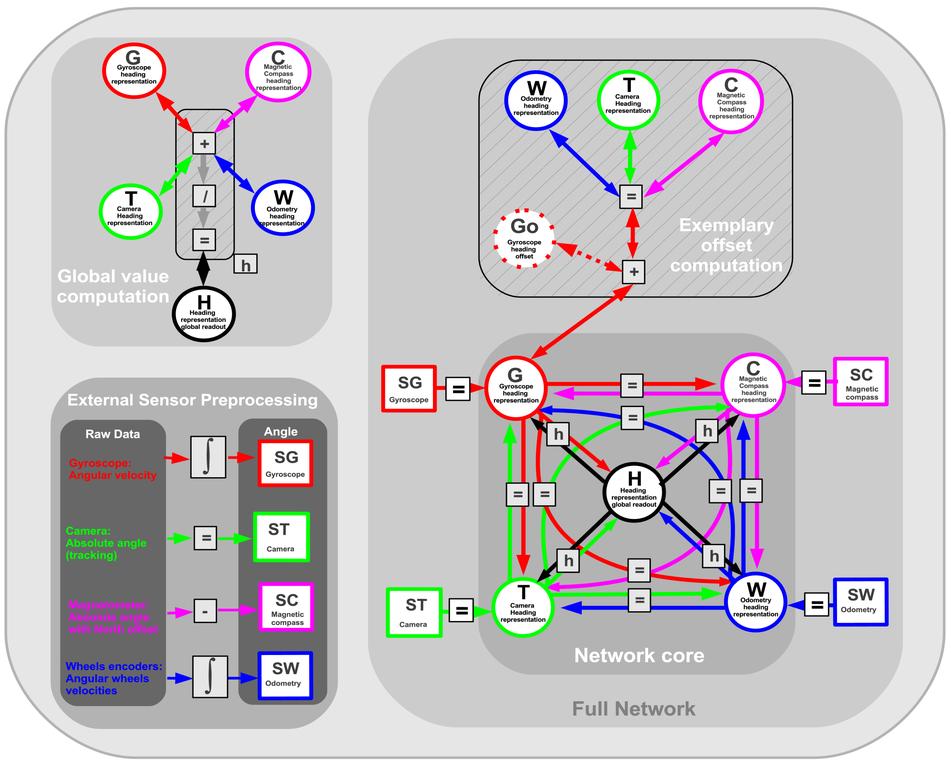

Fig. 3. The network architecture used in the 4 dimensional sensor fusion scenario

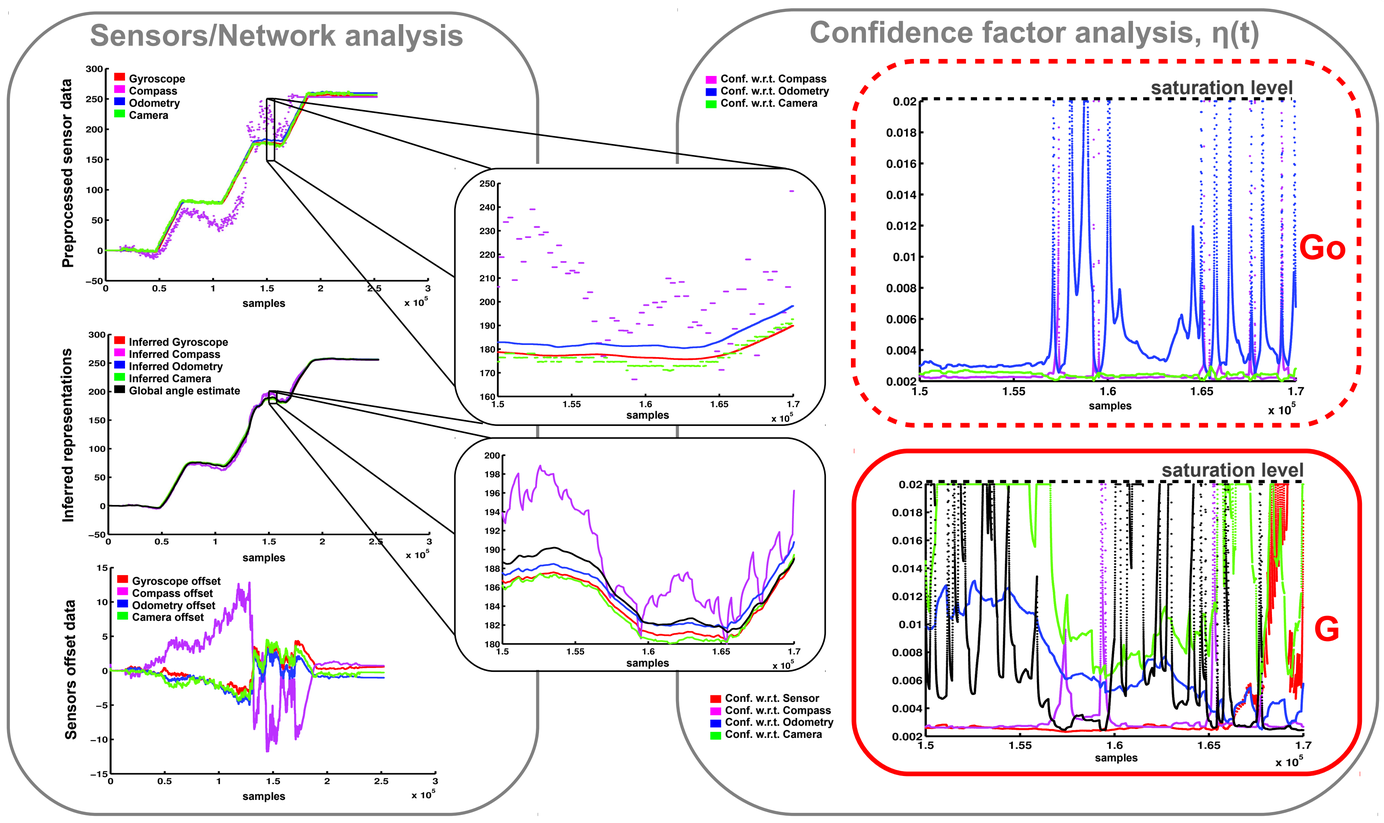

Fig. 4. Network analysis: inputs, inferred representations and offsets, and confidence factor adaptation

Dynamics and structure

network size: $n_i, i=1\ldots N \text{ nodes}$

connectivity: $n_i = n_j$, $h = 2(n_i+n_j+n_k+n_l)/N$

single node update: $\Delta n_j(t) = -\eta_{i,j} E_{n_i,n_j}(t)$

mismatch computation: $E_{n_i,n_j}(t) = n_i(t) - n_j(t)$

confidence factor adaptation:

$$\Delta \eta_{i,j}(t) = \eta_0 \frac{\sum_{k=1}^{N-i} E_{n_i,n_k}(t)}{(N-1)E_{n_i,n_j}(t)}$$

Features

- distributed **graphical network**
- **processing** and **exchanging** exclusively **local data**
- **dynamics** given by recurrent network **relaxation**
- **infer reliability** of sensory signals, similar to work in [3]

Experimental setup

- sensors' raw data **pre-processed** to align coordinate systems
- **offset nodes** compute **relative bias/offset** used to quantify the **changes in reliability**
- **global readout** node quantifies the **global estimate** of the network (its belief)
- each sensor data point presented for 100 iterations to allow **relaxation of the network**

Network behavior and results

- the network **infers** which sources of information to trust by considering **mismatch** between each **local belief** and **external information**
- the network continuously tries to **balance contributions** from each sensor to be consistent with the internal network belief using an **adaptive confidence factor**
- the **network "pulls" internal values** of the nodes towards a **unified value** compensating for drifts and inaccuracies in individual sensors

Future Work

Extensions to the existing structure

- **sparse representation (population code)** of quantities to **extract statistics** of the quantities
- **temporal** relationships (integration/differentiation) to **embed preprocessing** in the network
- **multidimensional** relationships and **integrate new** sensory **modalities**
- **learning** the relationships (network **topology**)

References:

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[3] Cook, M., Gugelmann, L., Jug, F., Krautz, C., Steger, A.: Interacting maps for fast visual interpretation. Proceedings of International Joint Conference on Neural Networks, 770-776 (2011).

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