Presentation of research interests

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Presentation of research interests at the Department of Computing, Mathematics and Physics, Western Norway University of Applied Sciences, Bergen, Norway, 2017

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About Me

Education:

- PhD in Engineering Cybernetics, Norwegian University of Science and Technology (NTNU), Norway
- MSc in Computer Science Engineering, University of Siena, Italy
- BSc degree in Computer Science Engineering, University of Catania, Italy

Mobility:

- Visiting Fellow, Technical Aspects of Multimodal Systems (TAMS), Department of Mathematics, Informatics and Natural Sciences, University of Hamburg, Hamburg, Germany
- Visiting Student, School of Computing and Intelligent Systems, University of Ulster, Londonderry, United Kingdom
- Granted with an Erasmus+ Staff Mobility for Teaching and Training project

Activities:

- Membership Development Officer for the IEEE Norway Section

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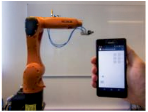
Research topics

Visualisation/Game Development

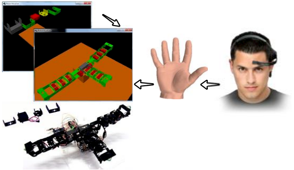
Augmented Reality/Virtual Reality

Micro-controllers, IoT, Maker Tech.

Mobile Device

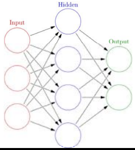


Software/Hardware Codesign



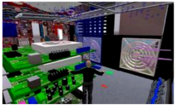
Real-time Systems

Artificial Intelligence



Safety-Critical Systems

Education



About Me

Current position:

- Filippo Sanfilippo, Postdoctoral Fellow at the Dept. of Eng. Cybernetics, Norwegian University of Science and Technology (NTNU), Trondheim, Norway

Current courses:

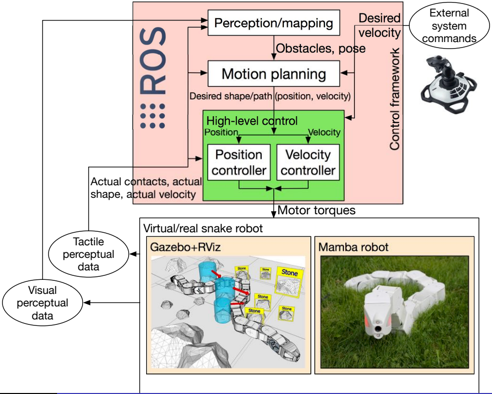
- TTK4235 - Embedded Systems (Lecturer)
- Experts in Teamwork - Snake robots (Supervisor)

Past courses:

- Real-time Computer Programming (Lecturer)
- Mechatronics, Robots and Deck Machines (Teaching Assistant)
- System Simulation in Matlab/Simulink (Lecturer)

Current research topic:

- "SNAKE - Control Strategies for Snake Robot Locomotion in Challenging Outdoor Environments", project number 240072, supported by the Research Council of Norway through the *Young research talents funding scheme*



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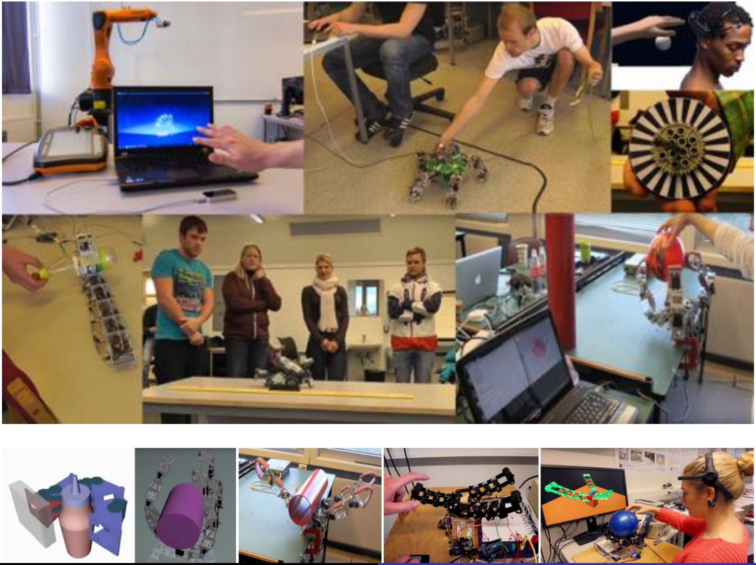
Student projects



Current maritime crane control architecture

Low control flexibility and non-standardisation are two crucial issues:

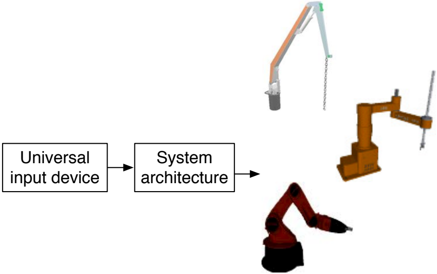
- relatively simple control interfaces;
- array of levers, throttles or buttons are used to operate the crane joint by joint;
- each input device can normally control only one specific crane model.

When considering working efficiency and safety, this kind of control is extremely difficult to manage and extensive experience with high control skill levels is required of the operators.

Currently used input devices

Underlying idea

A general architecture that allows for modelling, simulation and control of different models of maritime cranes and, more generally, robotic arms by using the same universal input device.



Main challenges:

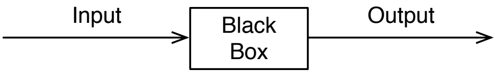
- mapping the fixed degrees of freedom of the universal input device to the variable degrees of freedom of the cranes or robots to be controlled;
- designing and testing different mapping procedures based on Machine Learning.

Machine learning procedures

- A common assumption in the previous literature is that the IK model of the arm to be controlled is a priori knowledge.
- This method is not very flexible, especially when planning to control different arms using a universal input device because several IK models are needed: one for each arm or crane to be controlled.

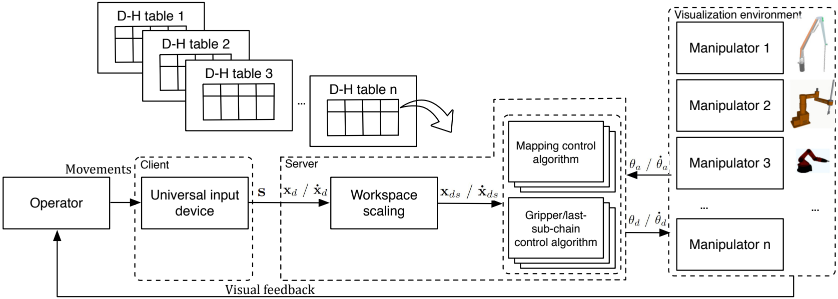
An alternative control method based on machine learning procedures:

- using methods that do not assume a priori knowledge for the IK model of the arm;
- In this way the system would be able to automatically learn the kinematic properties of different arms and new models could also be easily added.



Most of the previous works in this field are only able to learn the control of a specific crane/arm. No common universal input device to control various cranes/arms with different kinematics exists.

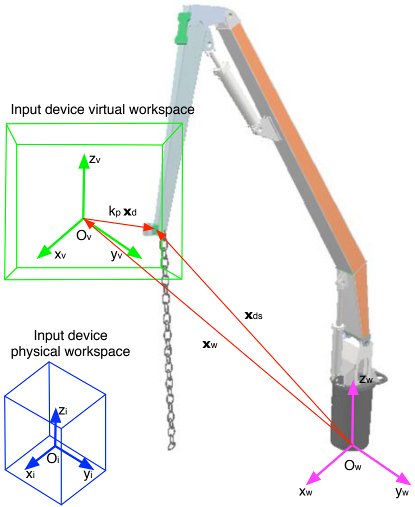
The proposed control system architecture, overview



The proposed architecture provides the possibility of controlling the arms in position mode or velocity mode[1].

[1] Filippo Sanfilippo et al. "A mapping approach for controlling different maritime cranes and robots using ANN". In: *Proc. of the IEEE International Conference on Mechatronics and Automation (ICMA)*. 2014, pp. 594–599.

The proposed control system architecture, workspace scaling



The proposed architecture allows for expanding and shifting the small-scale physical workspace of the input device to a virtual expanded workspace allowing the robot arm for more accurate and precise movements.

$$\mathbf{x}_{ds} = k_p \mathbf{x}_d + \mathbf{x}_w , \qquad (1)$$

where k_p is the position scaling factor and $\mathbf{x}_w$ is a shifting vector that defines the position of the virtual reference frame with respect to the global reference frame.

$$\dot{\mathbf{x}}_{ds} = k_v \dot{\mathbf{x}}_d , \qquad (2)$$

where, k_v is the velocity scaling factor.

The proposed control system architecture, mapping control algorithm

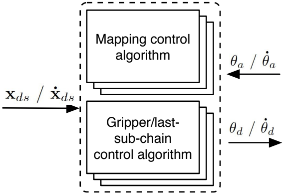
For all the different models to be controlled, the mapping methods have to implement the classic inverse kinematic functions that can be generalised as follows:

$$\theta_d = f_p^{-1}(\mathbf{x}_{ds}), \tag{3}$$

concerning position control, and

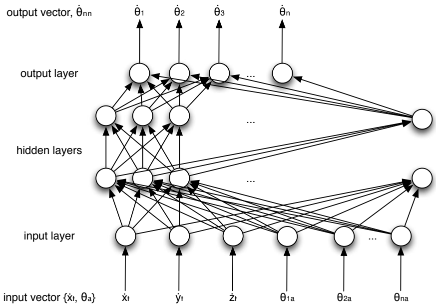
$$\dot{\theta}_d = f_v^{-1}(\theta_a, \dot{\mathbf{x}}_{ds}), \tag{4}$$

for velocity control, where θ_a is the the actual joint angles vector.



The proposed architecture also allows the end-effector to be modelled as a distinct sub-chain that can be controlled separately. In general, a mapping control method may or may not consider the control of the whole manipulator.

The proposed ANN architecture



- The system automatically learns the mapping function, (4), for the different manipulators to be controlled.
- This approach only requires the FK models.

- The unique feature of this method compared to previous works is that the same set-up of the proposed algorithm is adopted independently of which manipulator is being controlled and whether the selected control mode is position or velocity.
- When controlling each specific manipulator and once selecting the particular control mode, the same instance of ANN is continuously used.
- What differs are the semantics and the size of inputs and outputs which are dynamically and automatically set by the system.

The proposed ANN architecture

- The input vector is given by $\{\dot{\mathbf{x}}_t, \theta_a\}$, where $\dot{\mathbf{x}}_t$ is the target velocity whereas θ_a is the actual joint configuration.
- The target velocity, $\dot{\mathbf{x}}_t$, depends on the operation scenario and it is given by:

$$\dot{\mathbf{x}}_t \simeq \mathbf{x}_{ds} - \mathbf{x}_a, \tag{5}$$

  if operating in position control mode, where $\dot{\mathbf{x}}_a$ is the actual end-effector velocity.
- If instead operating in velocity control mode, it is given by:

$$\dot{\mathbf{x}}_t = \dot{\mathbf{x}}_{ds}. \tag{6}$$

- From the top side, the output vector, denoted by $\dot{\theta}_{nn}$, consists of the target joint velocities.
- The number of neurons in the input and output layers changes according to the number of DOFs of the manipulator to be controlled. The number of hidden neurons is experimentally chosen to be equal to 3/2 of the sum of the size of the input layer and the size of the output layer.

Error function, training data and training Process

$$MSE(\dot{\theta}_d, \dot{\theta}_a) = \frac{1}{n}\sum_{i=1}^{n}(\dot{\theta}_d - \dot{\theta}_a)^2. \tag{7}$$

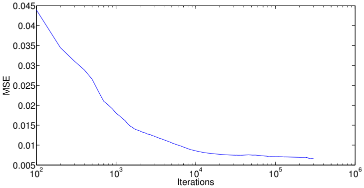
- Training data set: $(\{\dot{\mathbf{x}}_t, \theta_a\}, \dot{\theta}_{nn})$. In this specific case study, the Jacobian matrix is used. First, a set of samples is randomly generated in the Joint space, then the Jacobian matrix is built by using the differential approach. Successively, a set of random joint velocities is created and used to calculate the corresponding velocities in the Cartesian space.
- *Resilient Propagation* (RPROP) learning heuristic[2]. to overcomes the inherent disadvantages of pure gradient-descent. RPROP performs a local adaptation of the weight-updates according to the behaviour of the error function. This leads to an efficient and transparent adaptation process.
- According to the operational scenario, the output is obtained by:

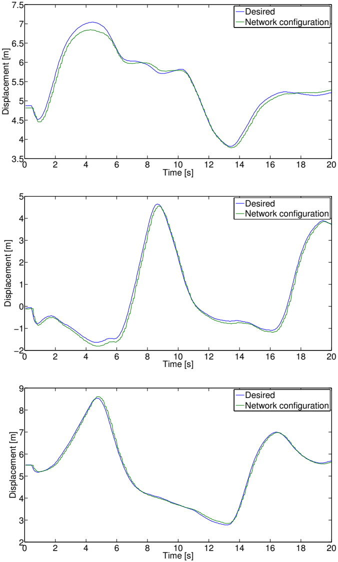
$$\theta_d = \int \dot{\theta}_{nn}\, dt, \tag{8}$$

$$\dot{\theta}_d = \dot{\theta}_{nn}. \tag{9}$$

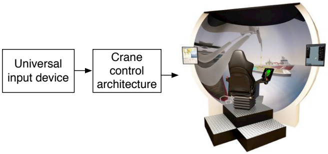
[2] Martin Riedmiller and Heinrich Braun. "A direct adaptive method for faster backpropagation learning: The RPROP algorithm". In: *Proc. of the IEEE International Conference on Neural Networks.* 1993, pp. 586–591.

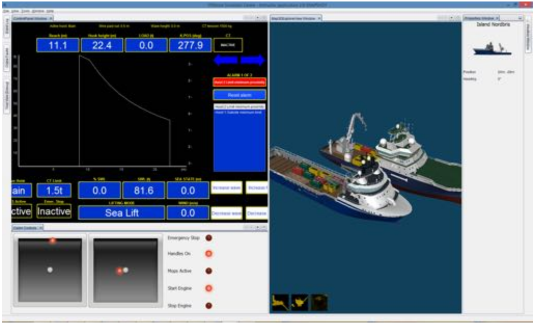
Simulation results





Simulation results





[3]

[3] Offshore Simulator Centre AS. *"OSC"*. 2014. URL: http://www.offsim.no/.

Demo

Conclusion and future work

Iteratively learning the IK properties of different arms:

- Using this approach, the system is able to automatically learn the IK properties of different models. Learning is done iteratively based only on observation of input-output relationships, unlike most other control schemes.

Compare different mapping methods:

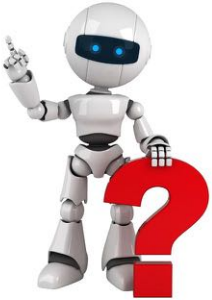
- Genetic algorithm (GA)[4].
- Particle Swarm Optimization (PSO)[5]
- JIOP, a machine learning framework that provides a selection of existing learning approaches and allows for implementing new algorithms has been developed by our research group[6].

[4] Filippo Sanfilippo et al. "A Universal Control Architecture for Maritime Cranes and Robots Using Genetic Algorithms as a Possible Mapping Approach". In: *Proc. of the IEEE International Conference on Robotics and Biomimetics (ROBIO), Shenzhen, China*. 2013, pp. 322–327.

[5] Filippo Sanfilippo et al. "A Benchmarking Framework for Control Methods of Maritime Cranes Based on the Functional Mockup Interface". In: *IEEE Journal of Oceanic Engineering* (2017).

[6] Lars Ivar Hatledal, Filippo Sanfilippo, and Houxiang Zhang. "JIOP: a Java Intelligent Optimisation and Machine Learning Framework". In: *Proc. of the 28th European Conference on Modelling and Simulation (ECMS), Brescia, Italy*. 2014, pp. 101–107.

Thank you for your attention



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References

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