Teaching Assembly forces:

The case of successful snap assembly

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Teaching assembly forces is challenging issue within the context of fast assembly robot deployment as it does not involve gross motions that can be captured by visual perception systems from human demonstrations. The feasibility of controlling an assembly task by teaching the correct assembly forces to a robotic system is an open issue. Collaborative human robot assembly and machine learning could be used in this direction. This presentation will aim to discuss the most promising directions by searching answers to a number of questions as well as describe a first attempt developed within the SARAFun project for the subproblem of **successful snap assembly detection**.

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Introduction

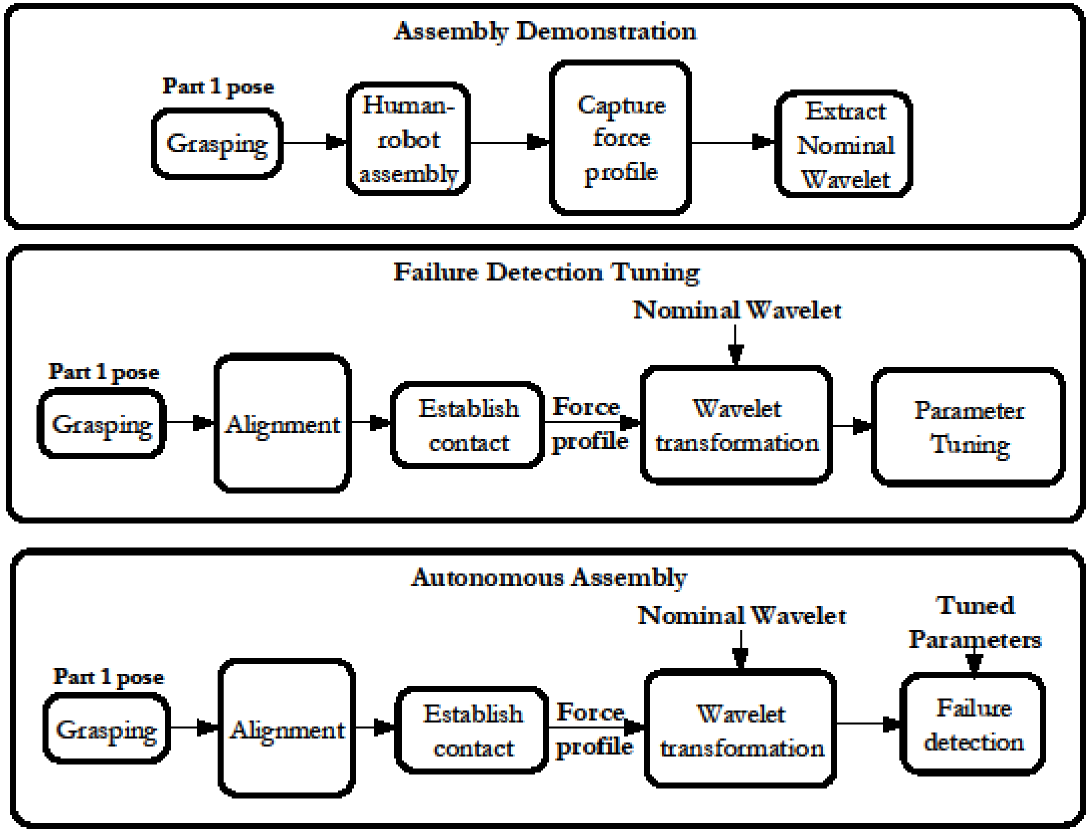
Motivation

- Contemporary assembly lines require increased adaptability with minimum external programming and tooling.
- Human-robot sharing of the work space opens new opportunities and challenges.
- Methods for fast robot deployment are required to reduce assembly set-up time.

Solution

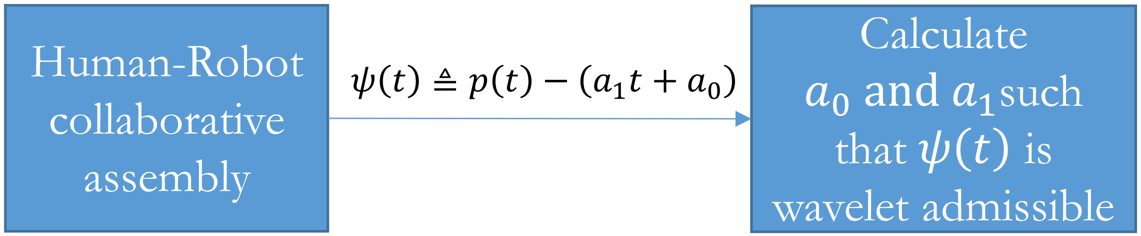
- Assembly task can be demonstrated by human.
- A Snap Assembly of two small parts involve contact forces developed between the mating parts that can be identified via human-robot collaborative assembly.
- Robot operates as a smart sensor capturing assembly forces.
- Human identifies successful assembly completion.

A Fast Deployment Strategy for Successful Snap Assembly Detection



Y. Koveos, D.Papageorgiou, S. Doltsinis, Z. Doulgeri, “A Fast Robot Deployment Strategy for Successful Snap Assembly”, 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS2016), At Tokyo Japan

Wavelet based pattern Identification



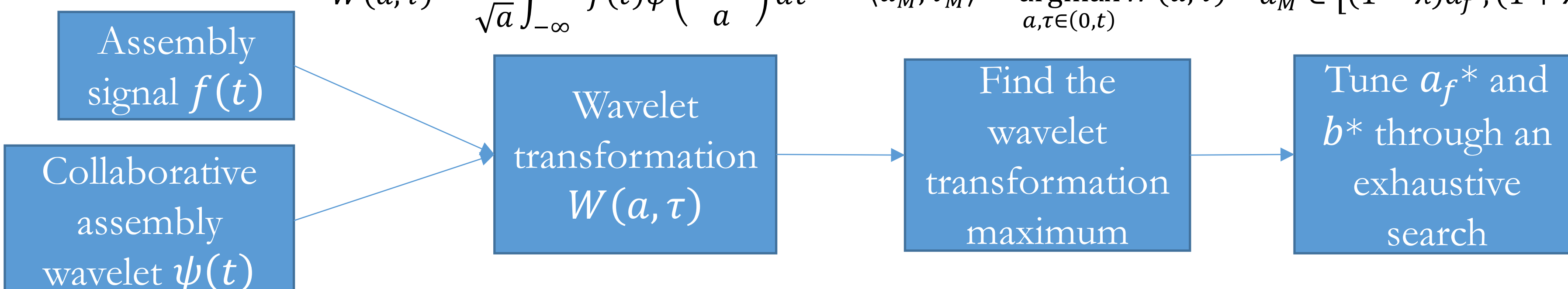
- $\psi(t) \in \mathcal{L}^1 \cap \mathcal{L}^2$
- $\int_{-\infty}^{+\infty} \psi(t)\, dt = 0$
- $\int_{-\infty}^{+\infty} |t\psi(t)|\, dt < +\infty$

- $p(t)$ is the captured force derivative during assembly

$$W(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-\tau}{a}\right) dt$$

$$\langle a_M, \tau_M \rangle = \underset{a,\tau\in(0,t)}{\operatorname{argmax}}\, W(a,\tau)$$

$$a_M \in \left[(1-\lambda)a_f\, , (1+\lambda)a_f\right]$$

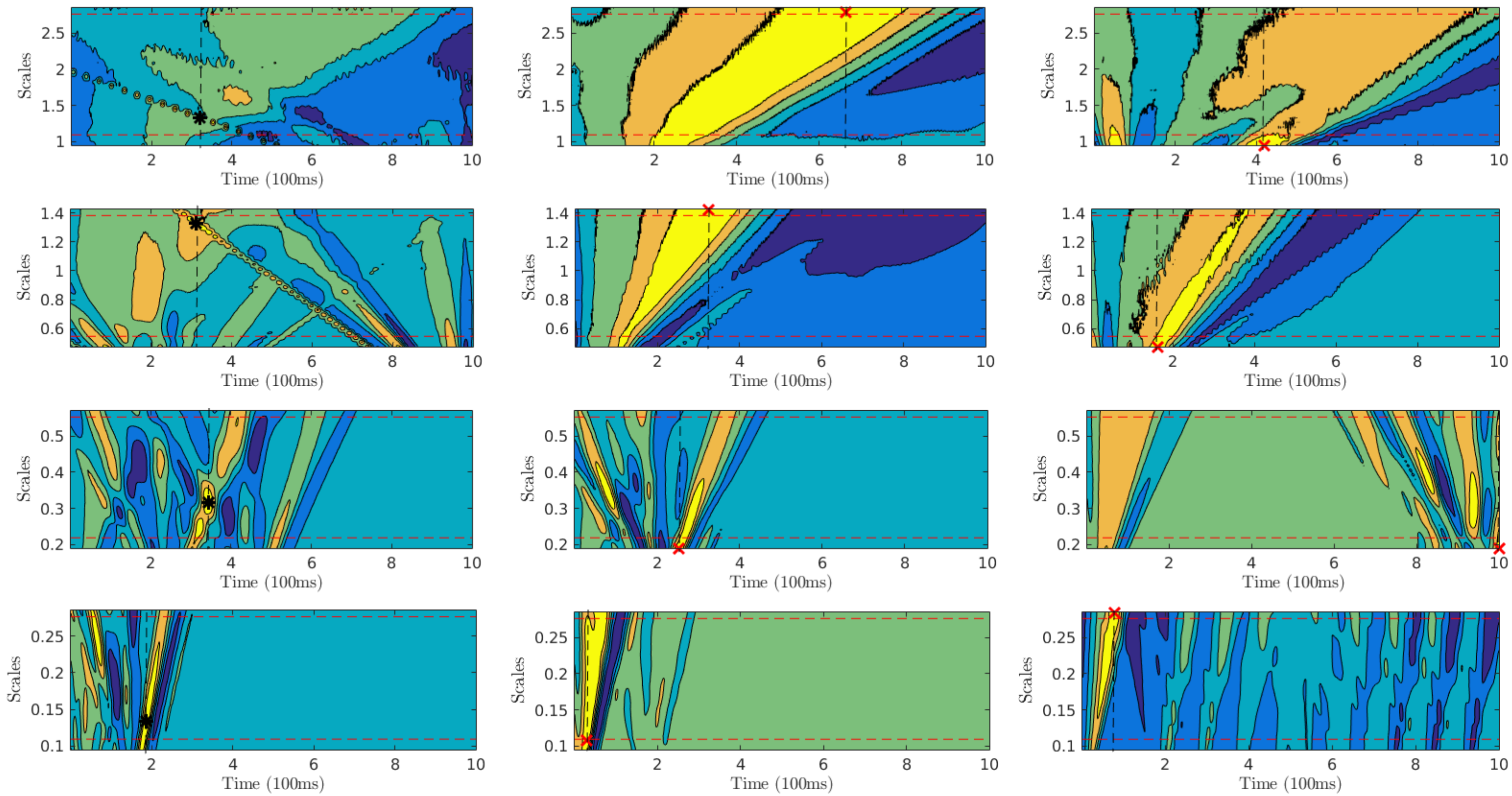


$\lambda, b \in [0,1]$, where b represents the human arm velocity during collaborative assembly

$^*a_f = \frac{b}{\|V_d\|}$, where $\|V_d\|$ the robot tip velocity

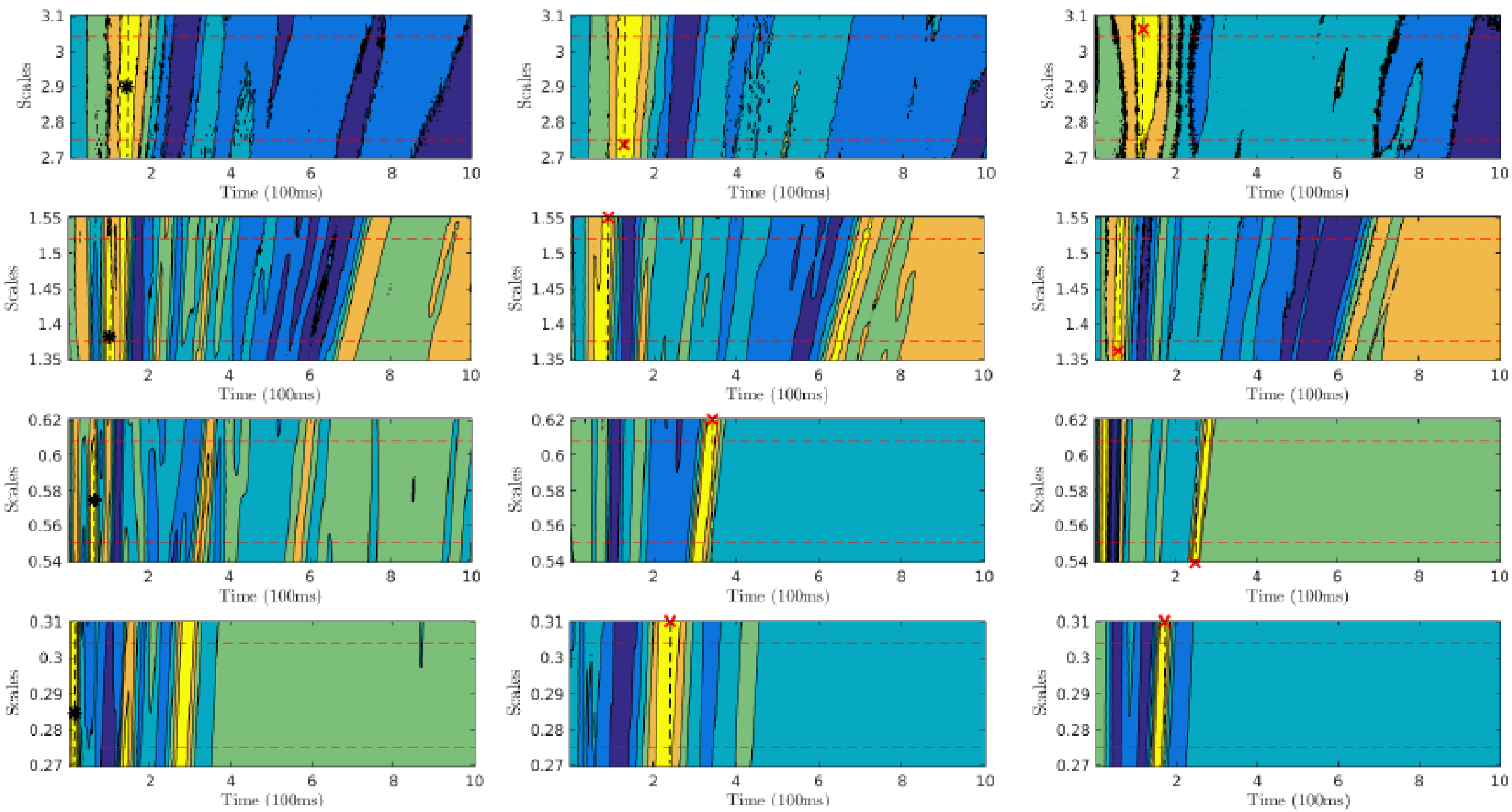
- Every new assembly signal should have a maximum a_M within the tuned limits to be successful.

Experimental Results (plugs)- Wavelets



- Rows indicate different assembly velocities (0.01, 0.02, 0.05, 0.1 m/s)
- Results for successful (column 1) and failed assemblies (column 2, 3)

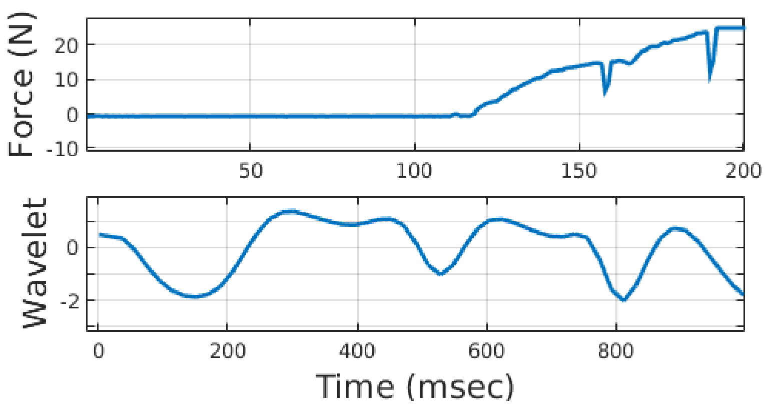
Experimental Results (Belts)- Wavelets



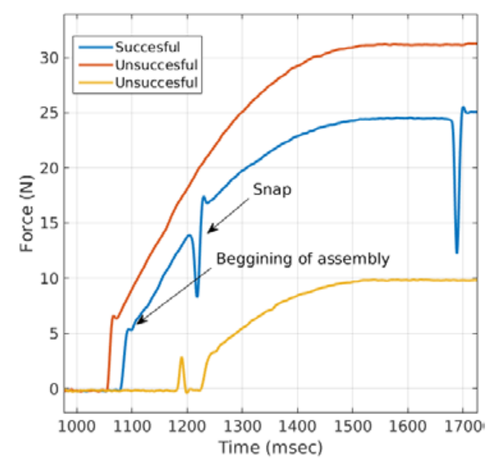
- Rows indicate different assembly velocities (0.01, 0.02, 0.05, 0.1 m/s)
- Results for successful (column 1) and failed assemblies (column 2, 3)

Experimental Results (electric plugs)– Assembly Forces

- Forces developed during human-robot assembly and extracted wavelet
  - Successful Snap assembly force has distinct features

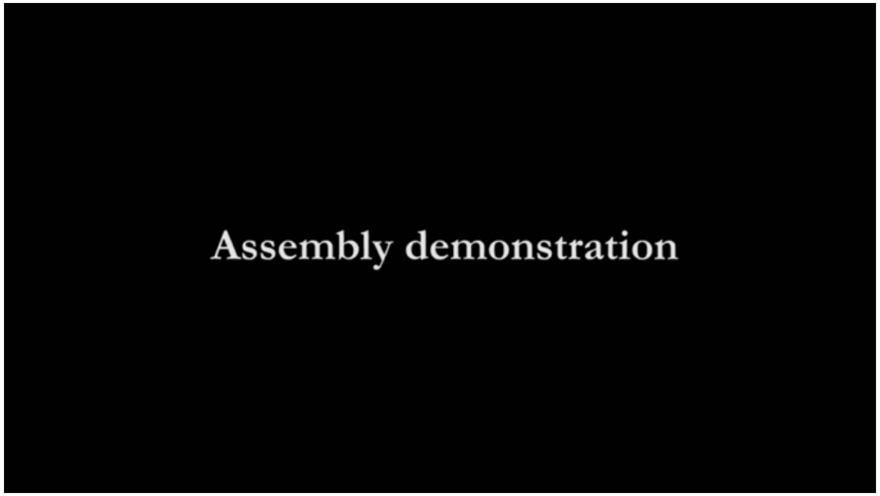


- Logged forces during successful and unsuccessful assemblies.
  - Wrong approaching angle
  - Insufficient force



Snap assembly
Implementation video

- Human robot collaborative assembly
- Autonomous Assembly



For the videos, please visit http://h2020sarafun.eu/erf-2017-tbd-for-industrialapplications/

Conclusions – Future Work

- A strategy focused on successful snap assembly detection was presented
- A robot can learn a pattern of forces from human-robot collaborative assembly by acting as a smart sensor
- Snap assembly forces allow generalization for different parts assembly (machine learning)
- Do different phases of other assembly types allow successful detection in a similar manner (force based)?
- Could we use real-time methods to adapt the control strategy and increase success rates?