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Data-Driven Goal Recognition in Transhumeral Prostheses Using Process Mining Techniques

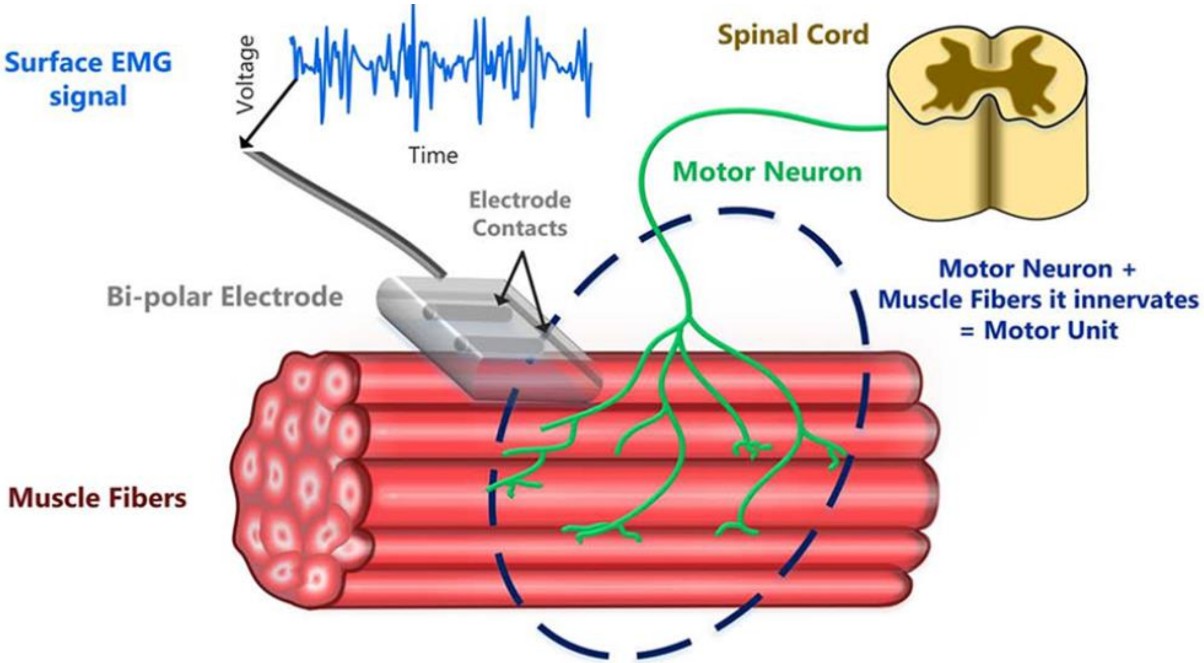
Zihang Su, Tianshi Yu, Nir Lipovetzky, Alireza Mohammadi, Denny Oetomo, Artem Polyvyanyy, Sebastian Sardina, Ying Tan, Nick van Beest

5th International Conference on Process Mining, October 23-27, 2023, Rome

Active Transhumeral Prostheses

Active prostheses are robotic devices with actuators (e.g. electric motors).

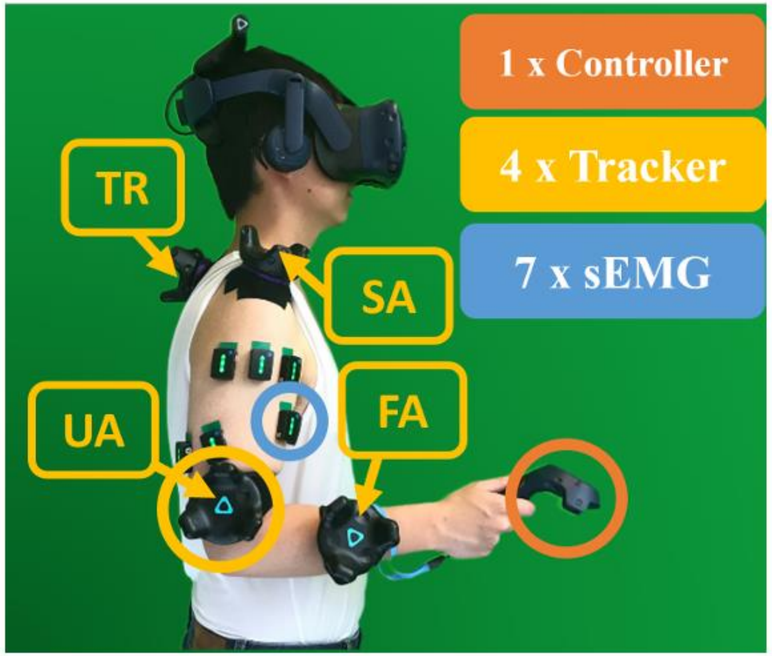
Aim to replace missing limb segments below the shoulder, restoring upper limb function for achieving specific prosthetic poses (target pose).

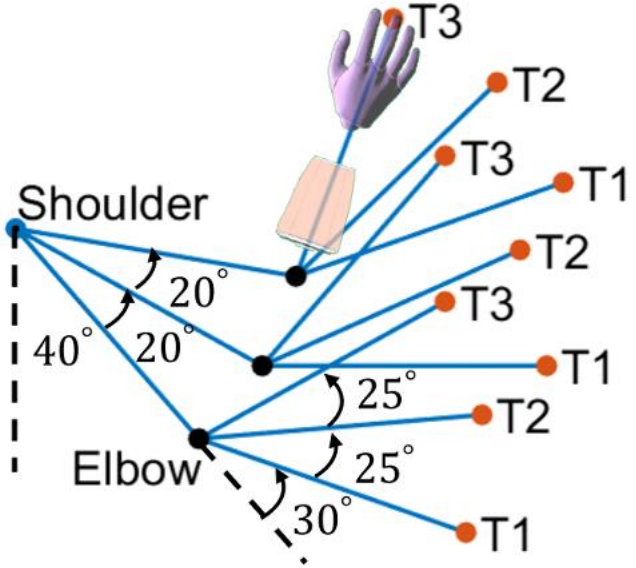


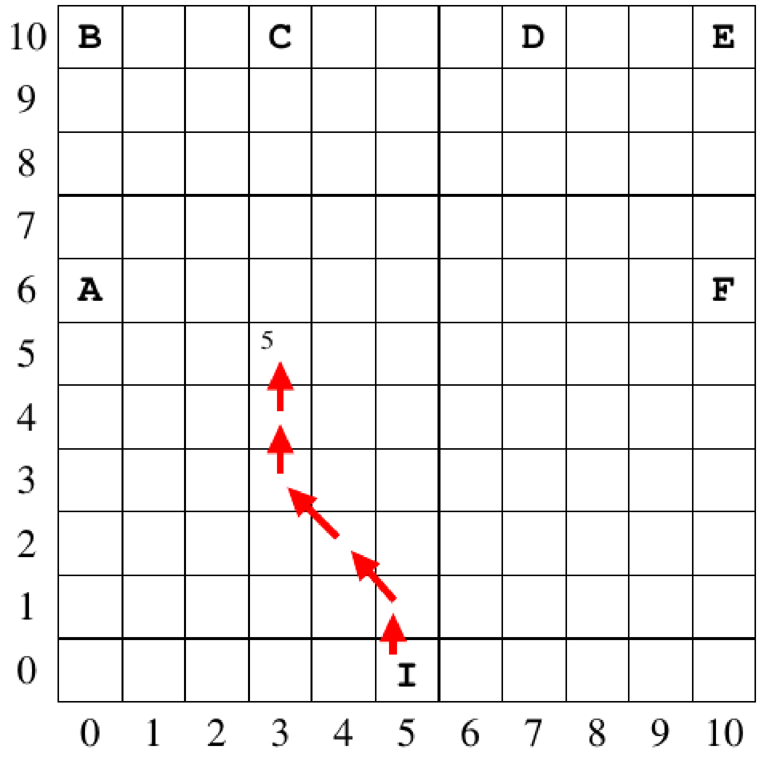
McManus, L., De Vito, G., & Lowery, M. M. (2020). Analysis and biophysics of surface EMG for physiotherapists and kinesiologists: Toward a common language with rehabilitation engineers. *Frontiers in neurology*, *11*, 576729.

Goal Recognition

Goal Recognition (GR) techniques aim to infer the intentions of an autonomous agent according to the observed actions of that agent [1].







1. H. A. Kautz, J. F. Allen, Generalized plan recognition, in: AAAI, 1986, pp. 32–37.

Existing Goal Recognition Approaches

Planning-based GR techniques rely on domain models and planners [1]

- Require domain experts to define the domain

Learning-based GR: Long Short-Term Memory Neural Network (LSTM) [2]

- Require large dataset for training the model
- Not explainable

Our approach: process mining (PM-)based GR [3,4]

- Can learn from traces; Perform well for small dataset [4]; Explainable
- But it is developed for categorical data (actions or events)

1. M. Ramirez, H. Geffner, Probabilistic plan recognition using off-the-shelf classical planners, in: Proc. of AAAI, 2010, pp. 1121–1126.
2. W. Min, B.W. Mott, J. P. Rowe, B. Liu, J. C. Lester, Player goal recognition in open-world digital games with long short-term memory networks, in: IJCAI, 2016, pp. 2590–2596.
3. A. Polyvyanyy, Z. Su, N. Lipovetzky, S. Sardina, Goal recognition using of-the-shelf process mining techniques, in: AAMAS, 2020, pp. 1072–1080.
4. Z. Su, A. Polyvyanyy, N. Lipovetzky, S. Sardina, and N. van Beest, Fast and accurate data-driven goal recognition using process mining techniques, Artificial Intelligence, vol. 323, p. 103973, 2023.

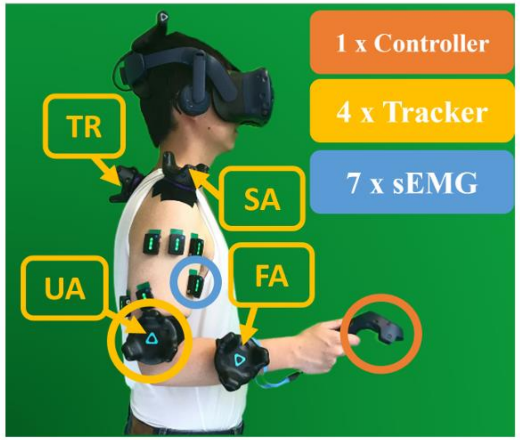
Apply PM-based GR to Prosthesis Scenario

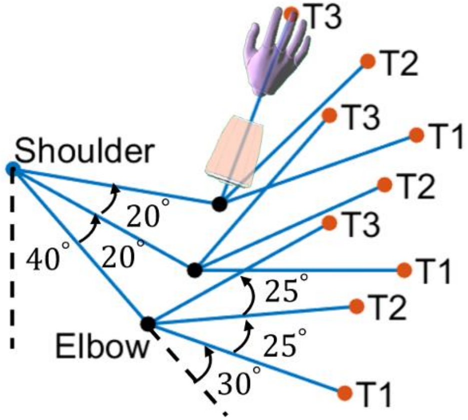
Input: Kinematics and Electromyography (EMG) signals (a sequence of signals from multiple sensors).
Frequency: 10 Hz (0.1 second per data point)

Goal: recognize the angle of elbow, three target elbow poses (T1, T2, T3)

Trace	Goal	f_1	f_2	f_3	...	f_{29}	f_{30}
1	T1	5.19727337	7.02395793	0.00254431	...	5.39759498	-0.3722619
1	T1	7.76278776	8.08816201	0.00472689	...	1.01557531	1.37592798
1	T1	13.4185557	8.87159453	0.00821896	...	-4.0004147	1.65328609
1	T1	22.0916619	9.04377674	0.01015369	...	-5.5399488	-1.7805512
1	T1	31.3641039	9.3586209	0.009165	...	-3.5156837	1.36367015
1	T1	38.2312577	10.139119	0.00616715	...	-1.4720033	5.87820456
1	T1	42.0592085	10.8827908	0.00315491	...	-0.3338844	4.29640897
2	T1	7.39110795	6.07336937	0.00064332	...	2.92403705	1.46698529
2	T1	10.5229866	7.44734189	0.00194998	...	1.60034347	2.94734496
...	...	...	...	...	...	...	...
6	T2	64.1830578	25.2975943	-0.0003433	...	-1.1970367	0.92412363
6	T2	66.8916142	27.5304609	-0.0017204	...	0.31022101	0.95595258

Table I





Feature Selection & Event Discretization

Trace	Goal	f_3	f_6	...	f_{27}	f_{30}	Event
1	T1	0.002544311	0.121301538	...	9.057075924	-0.372261852	e_0
1	T1	0.004726894	0.210557727	...	10.55266625	1.375927982	e_6
1	T1	0.008218956	0.391712037	...	4.416704571	1.653286092	e_5
1	T1	0.010153689	0.327711654	...	1.372325318	-1.780551234	e_2
1	T1	0.009165	0.311548058	...	5.526959903	1.363670147	e_5
1	T1	0.00616715	0.734098175	...	8.869853729	5.87820456	e_6
1	T1	0.003154906	1.227944362	...	4.916643199	4.296408971	e_8
2	T1	0.000643317	0.103164637	...	12.86040763	1.466985286	e_8
2	T1	0.001949978	0.336630569	...	13.45204634	2.94734496	e_6
...	...	...	...	...	...	...	...
6	T2	-0.000343322	0.410761081	...	23.78469914	0.924123631	e_4
6	T2	-0.001720367	0.504684583	...	21.08908217	0.955952575	e_3

Table II

K-Means

Process Mining-based Goal Recognition

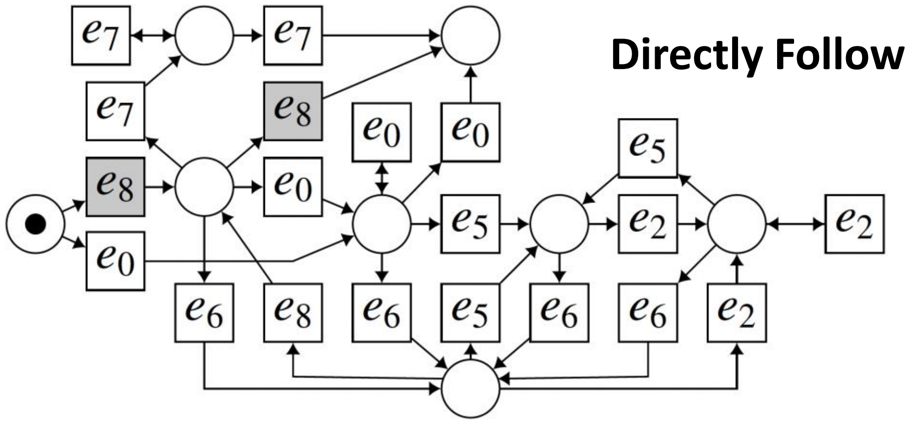


Fig. 4: Process model M_1 discovered from even log L_1.

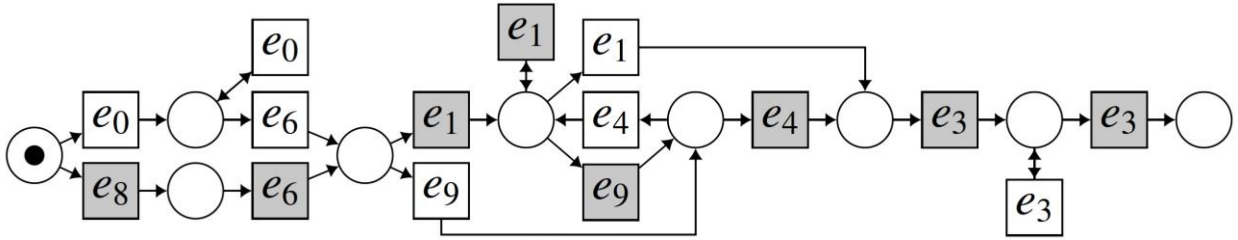


Fig. 5: Process model M_2 discovered from even log L_2.

Directly Follow Miner [1]

Current Observation

$$\tau = \langle e_8, e_6, e_2, e_1, e_1, e_9 \rangle$$

Optimal Alignments [2]

$\sigma_1 =$

τ	e_8	$\gg$	e_6	e_2	e_1	e_1	e_9
M_1	e_8	e_8	$\gg$	$\gg$	$\gg$	$\gg$	$\gg$

$\sigma_2 =$

τ	e_8	e_6	e_2	e_1	e_1	e_9	$\gg$	$\gg$	$\gg$
M_2	e_8	e_6	$\gg$	e_1	e_1	e_9	e_4	e_3	e_3

1. S. J. J. Leemans, E. Poppe, M. T. Wynn, Directly follows-based process mining: Exploration & a case study, in: ICPM, 2019, pp. 25–32.
2. A. Adriansyah, N. Sidorova, B. F. van Dongen, Cost-based fitness in conformance checking, in: ACSD, 2011, pp. 57–66.

Alignment Weights & Probability Distribution

Smooth factor | Asynchronous suffix penalty | Discount factor | Cost of asynchronous move

$$\omega(\tau, M_G) = \phi + \lambda^m \times \sum_{i=1}^{n} \left(i^{\delta} \times c(\tau, M_G, i) \right)$$

$$\Pr(G \mid \tau) = \frac{e^{-\beta \times \omega(\tau, M_G)}}{\sum_{G' \in \mathcal{G}} e^{-\beta \times \omega(\tau, M_{G'})}}$$

P(T1 | τ) = 0.06

P(T2 | τ) = 0.94

To optimize these parameters: PRIM algorithm [1]

1. Z. Su, A. Polyvyanyy, N. Lipovetzky, S. Sardina, and N. van Beest, Fast and accurate data-driven goal recognition using process mining techniques, Artificial Intelligence, vol. 323, p. 103973, 2023.

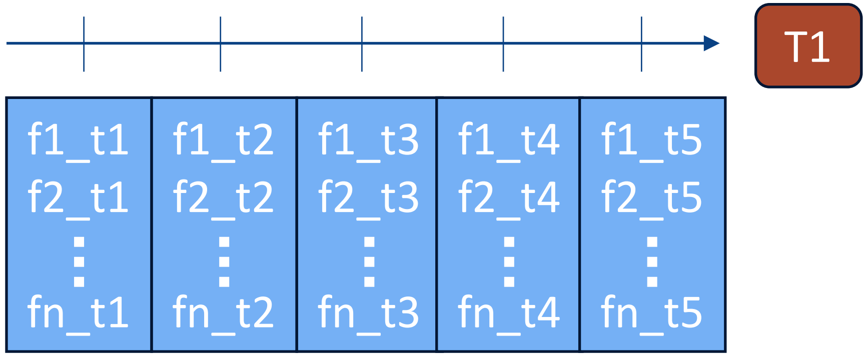
Experiment Settings

Benchmarks: long short-term memory (LSTM) [1], linear discriminant analysis (LDA).

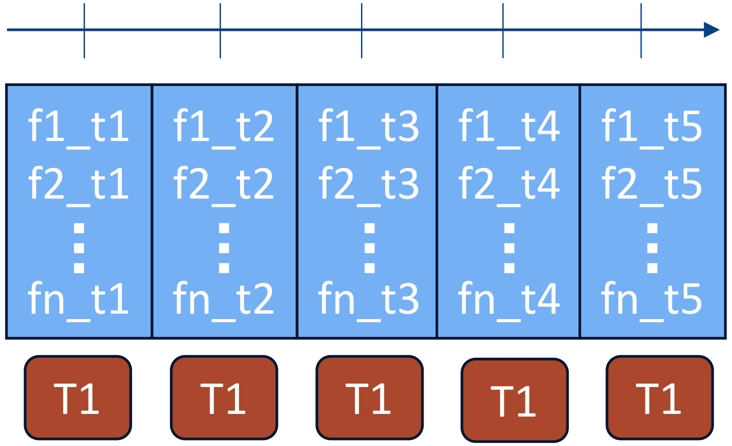
Cross validation: 10 subjects, 90 traces for each subject, 30 traces per goal (target pose).

- Testing set (3 traces)
- Training set (the remaining 87 traces)

Labelled training data



LSTM, PM-based GR



LDA

1. Huang, J., Li, G., Su, H., & Li, Z. (2021). Development and continuous control of an intelligent upper-limb neuroprosthesis for reach and grasp motions using biological signals. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(6), 3431-3441.

Quality Measurement

The fraction of the correctly inferred goals among all the inferred goals:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

The fraction of the correctly inferred goals among all the true goals:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

For each subject, we test performance on different levels of observation: 10%, 30%, 50%, 70%.

Results and Conclusions

Obs%	PM		LSTM	LDA
	p	r	$p = r$	$p = r$
10%	0.344 ± 0.009	**0.946** ± 0.015	**0.348** ± 0.031	0.336 ± 0.031
30%	**0.426** ± 0.020	**0.813** ± 0.026	0.390 ± 0.032	0.346 ± 0.031
50%	**0.486** ± 0.024	**0.754** ± 0.028	0.427 ± 0.032	0.353 ± 0.031
70%	**0.592** ± 0.026	**0.789** ± 0.027	0.484 ± 0.033	0.523 ± 0.033

TABLE V: Average precision (p) and recall (r) for all subjects

The results from the t-tests indicate that the average precisions and recalls for different approaches are significantly different from each other at a 95% confidence level (Šidák correction is considered).

Probability gap is the difference between:

- The max probability that our inferred by our system.
- The probability associated with the ground truth.

PM: 0.064
LSTM: 0.277
LDA: 0.623

These results indicate that the PM-based GR system exhibits less confidence when making mistakes than the other two benchmarks.

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End

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