Manipulation Behaviors and Skill Learning

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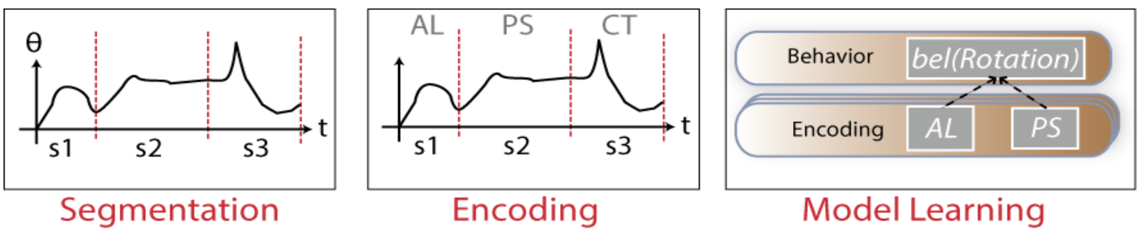
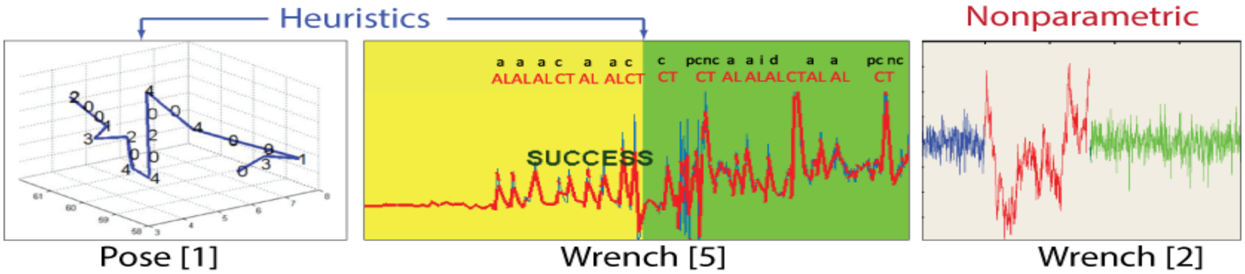
Overview: This work focuses on the characterization of enacted tasks and sub-tasks as well as the skill with which these were executed. In effect we are trying to learn the following two questions: what did the robot do (at a high level of abstraction)? And, how did he do it (i.e. the quality of the motion)? This sets the stage for attempting to improve the quality of the motion as well as higher level planning and reasoning about the latter as well. The basis for our approach is the extraction of primitives from sensor data: both from pose information and wrench information. Such primitive information contains intrinsic information about the manipulation motion and can be uniquely encoded and represented as a string set. Such string set is then representative of not only the task (or sub-task) but the way in which the task is accomplished. Once the string encoding is in place, we are able to use contextual information along with probabilistic tools to learn the corresponding behavior and skill models. Fig. 1 shows an overview for manipulation behavior and skill learning.



Segmentation: Signal segmentation for manipulation tasks can be executed both in the pose domain or the wrench domain. In our experience, there are two overarching approaches: heuristic approaches exploiting domain knowledge, and more generic approaches involving non-parametric probabilistic approaches. For heuristic methods, 3D pose (position and orientation independently) can be discretized into a set of locally assigned frames using Frenet-frame (FF) related capture relative curvature changes [1]. As for wrench data, the latter can be discretized independently for each axis by fitting the data with a series of straight line segments whose gradients are used to capture relative force change [5]. Heuristic methods as the ones just presented, rely on predefined components, like thresholds to transition between a task's states. In this regard, nonparametric Bayesian methods can be used capture the full evolution of signals and characterize them in a probabilistic way, making it a more robust approach. Nonparametric Bayesian approaches are very effective at segmenting data very naturally [2]. Prior processes like the Hierarchical Dirichlet process, effectively segments the signal according to the complexity of the data. It is the observation models, in particular, that the modelling of the evolutionary signal takes place. Knowledge-based pose/wrench

Encoding: With regards to encoding the heuristics: the quantized segments of pose data via FF related techniques can be represented through a coded string mapping each segment to a small set of *canonical directions*, known as Descriptive Curve Coding. The size of the dictionary depends on the FF technique used and the granularity of the quantization [1]. On the other hand, the wrench data's main feature is its force changes, best captured by the gradient of the fitted curve. As with the pose, here too, the force's relative change can be encoded through a small set of gradient partitions [5]. However, with the wrench data, it has been proven useful to use a hierarchical taxonomy on which primitives are abstracted iteratively. The first abstraction gives rise to actions with its own canonical set of labelled actions, and the next and last layer gives rise to behaviors with its own set of labelled behaviors as well. With regards to the nonparametric Bayesian approaches, encoding can take place by characterizing the parameters associated with the observation models: be it a Gaussian distribution, or Markov Switching Processes which use state-space models. The key principle is that the strings sets, in whichever domain, inherently characterize sub-tasks (and consequently the task) as well as the skill level.



Classification: With regards to classification, we need to make the best use of existing tools in machine learning and probability to best separate classes. For the heuristics: pose strings sets have been classified by extracting a *longest common string* across pairs of trials and using similarity metrics that then can be fed into a classifier like an SVM for determination. For wrench data, an SVM classifier was used on feature vectors composed from labels at different levels of abstraction in the hierarchical taxonomy (see *Encoding*) giving very good results [3]. Similarly, Bayesian filters have been used to generate beliefs about the task's state [4]. For the nonparametric Bayesian approaches, the log-likelihood probability of the wrench data given a class can be used to produce beliefs for each class, then selecting that which has the highest likelihood.

Skill Classification: Skill classification only makes sense when skill levels can be differentiated (i.e. novice, intermediate, expert). In order to generate skill levels there are two approaches: objective and subjective. For the former, one might look at specific fields (e.g. medical surgery) to find industry-approved standards for the human counterpart. Then, a surgical robot's performance can be evaluated and correlated to a specific skill level. For the latter, subjective assessment needs supervised classification, where a user labels different tasks to different level sets. Once there are skill levels, we can use our sets of encoded strings to correlate data to a given skill level but also gain insight into what are the main features of each skill level.

References

[1] Narges Ahmidi, Yixin Gao, Benjamn Béjar, S Swaroop Vedula, Sanjeev Khudanpur, René Vidal, and Gregory D Hager. String motif-based description of tool motion for detecting skill and gestures in robotic surgery. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013*, pages 26–33. Springer, 2013.

[2] Emily B Fox, Erik B Sudderth, Michael I Jordan, and Alan S Willsky. Bayesian nonparametric methods for learning markov switching processes. *Signal Processing Magazine, IEEE*, 27(6):43–54, 2010.

[3] Weiqiang Luo, J. Rojas, TianQiang Guan, K. Harada, and K. Nagata. Cantilever snap assemblies failure detection using svms and the rcbht. In *Mechatronics and Automation (ICMA), 2014 IEEE International Conference on*, pages 384–389, Aug 2014.

[4] J. Rojas, K. Harada, H. Onda, N. Yamanobe, E. Yoshida, K. Nagata, and Y. Kawai. Probabilistic state verification for snap assemblies using the relative-change-based hierarchical taxonomy (in-print). In *IEEE-RAS Intl. Conf. on Humanoid Robots*, 2012.

[5] Juan Rojas, Kensuke Harada, Hiromu Onda, Natsuki Yamanobe, Eiichi Yoshida, Kazuyuki Nagata, and Yoshihiro Kawai. Towards snap sensing. *International Journal of Mechatronics and Automation*, 3(2):69–93, 2013.