Probabilistic State Verification for Snap Assemblies using the Relative-Change-Based Hierarchical Taxonomy.

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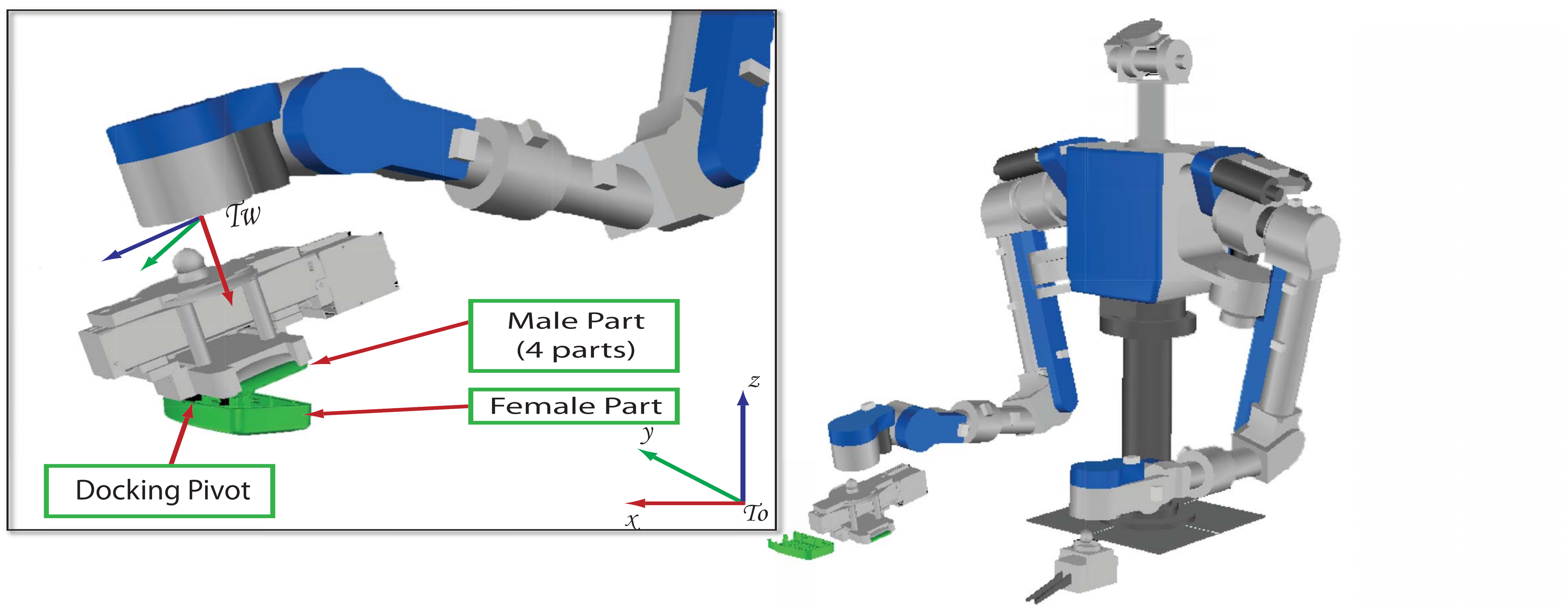
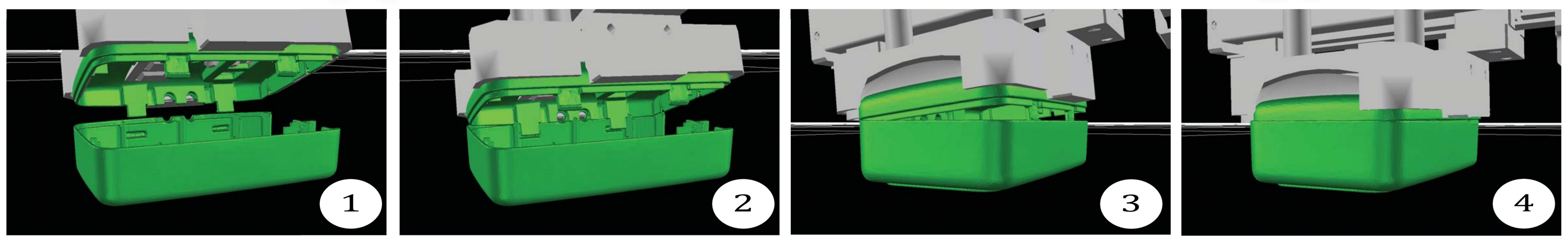
Introduction



Snap Assemblies are challenging due to varied geometrical configurations of elastic components. Cantilever snap types have 1, 2, 4, or more snaps. Our goal is to develop a Snap Sensing framework that perform state estimation and error -corrective motions.

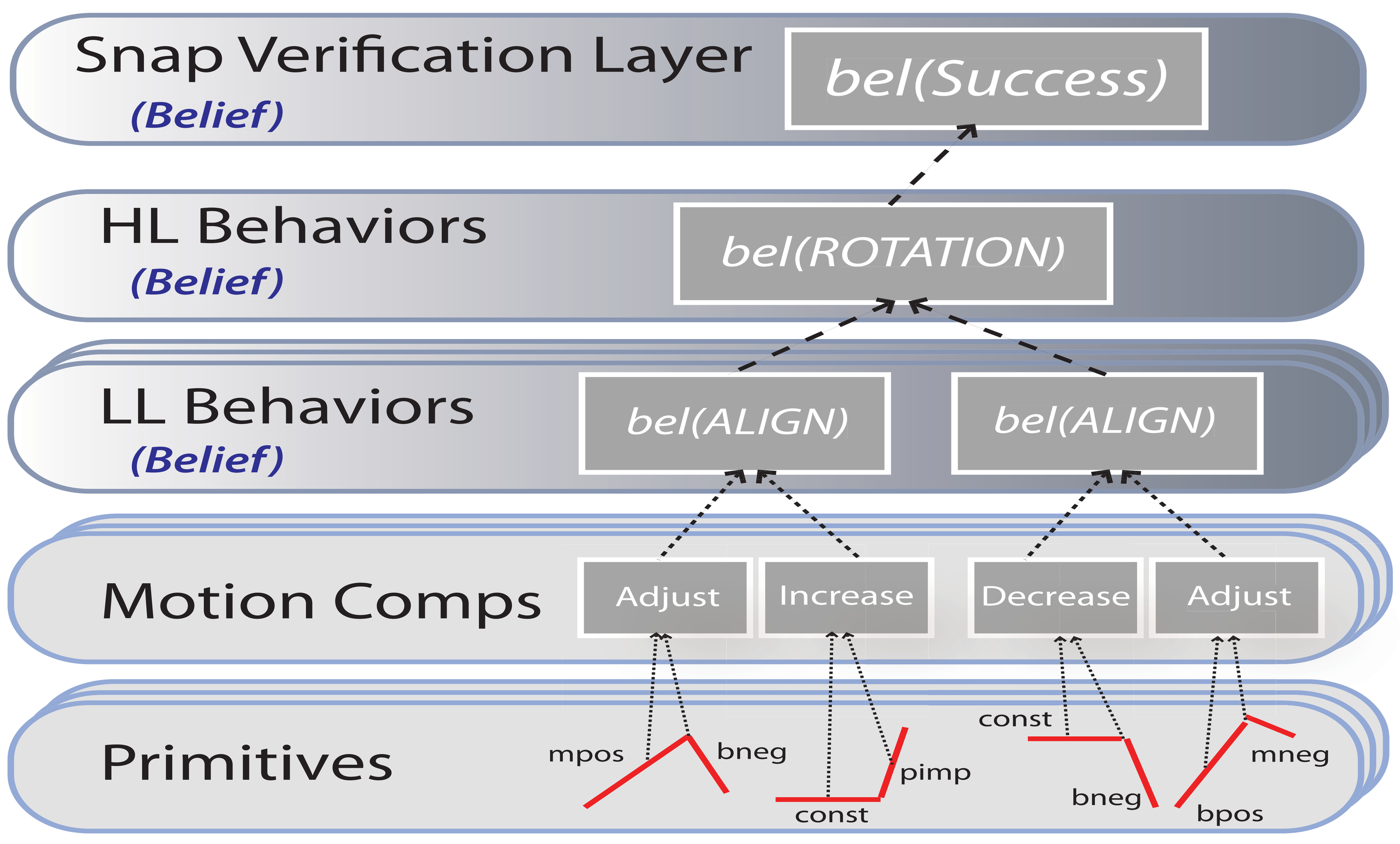
A control strategy, a hierarchical taxonomy, and Bayesian filtering were integrated to produce robust and intuitive robot state representations needed for corrective motions.

Pivot Approach Control Strategy



The PA exploits snap parts' hardware design to constrain the task's motion and generate similar sensory-signal patterns across trials & systematically discretize the assembly into intuitive states.

RCBHT



The RCHBT yields state representations by hierarchically abstracting FT relative-change to generate intuitive HLBs. Patterns are classified through a small set of categoric labels in contextually sensitive ways across each automata state in the Pivot Approach for all 6 FT axes.

Bayesian filtering (BF) was embedded from the 3rd layer -up yielding belief states for each LLB. The HLB layer computed joint probabilities of key LLBs to yield an outcome assessment scheme for the task.

Probabilistic RCBHT

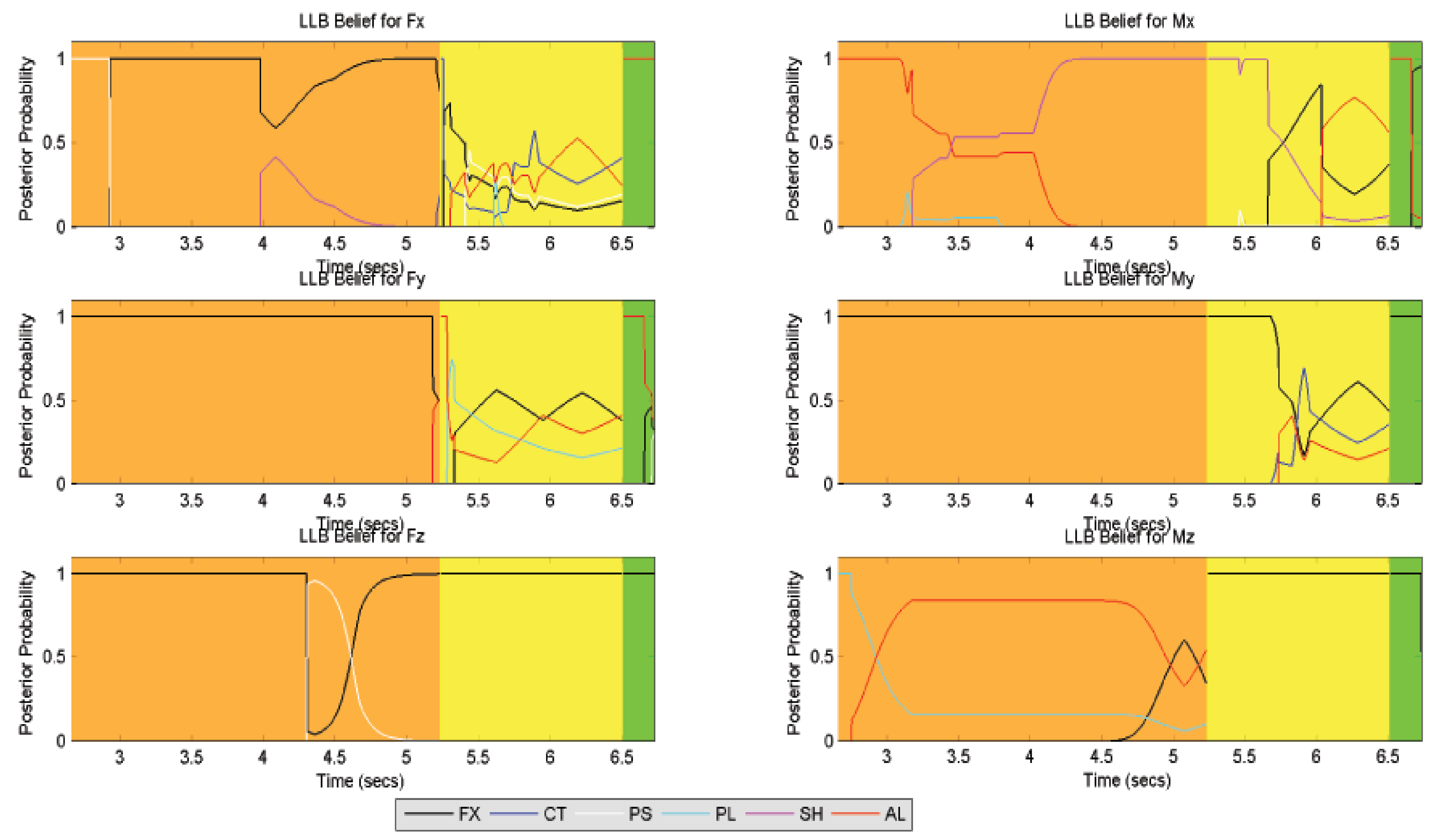
Including bayesian filtering in the RCBHT deals with uncertainty and renders more intuitive and granular understanding of the robot's state. The pRCBHT computes a belief state for each LLB for each automata state for each FT axis.

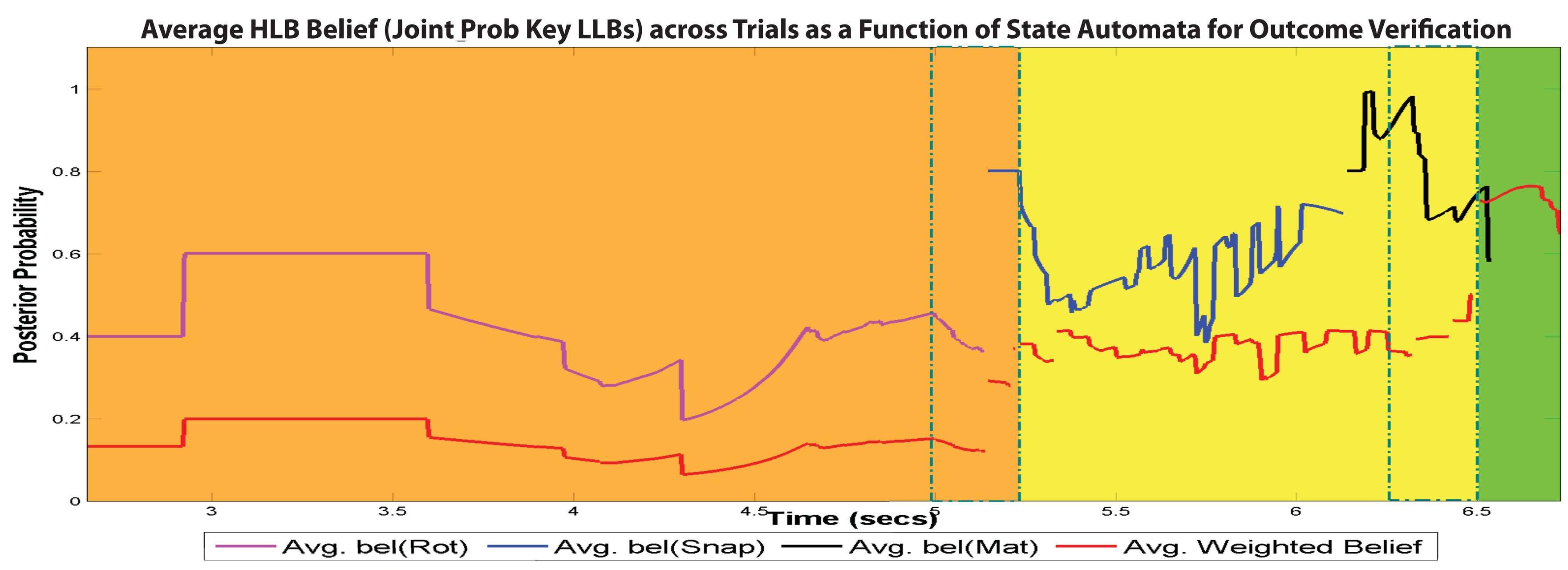
The current belief state is updated recursively from the previous state by means of a Prediction Step and a Correction Step. The latter predicts the state by using a system model from the previous time-step. The former updates the prediction by incorporating an observed measurement. In our work, we observed the cumulative duration of individual llb's and computed a probability using a Gaussian distribution such that:

$$
\begin{aligned}
P(llb_{i,t}|z_{llb,1:t}, u_{1:t-1}) = \\
\eta P(z_{llb,t}|llb_{i,t}) \sum_{j,t-1} P(llb_{i,t}|llb_{j,t-1}, u_{t-1}) \\
P(llb_{j,t-1}|z_{1:t-1}, u_{1:t-1})).
\end{aligned}
$$

Results

Two plots below: 1) Shows continous LLB beliefs for all states and FT axes. See legend for classification. 2) Shows an Outcome Assessment Verification Scheme. HLBs were computed as the joint probabilities of key LLB beliefs. The scheme predicts wether each state is successful or not.





Conclusion

A prob snap state estimation system was presented as part of the development of a Snap Sensing framework. The pRCBHT rendered a more robust system by providing belief states and correct evaluation of all test assemblies.