Spatial-Temporal Online Learning with Sliding Window in Gaussian Processes for Tactile Object Classification

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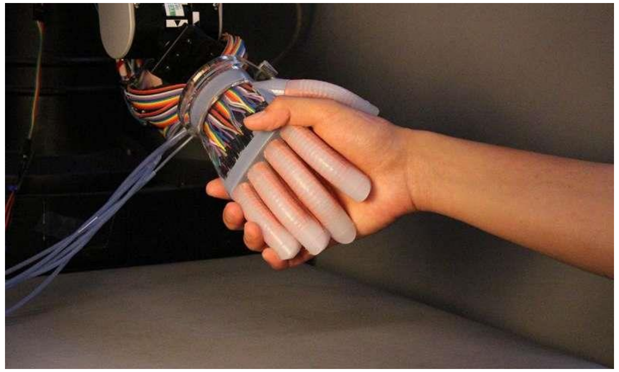
Motivation



Human Robot Interaction

Object Recognition

Texture Recognition

- In many robotic tasks such as Human Robot Interaction, Objection and Texture Recognition, tactile sensors play important role to interact with world.
- In this project, we focus on object recognition by tactile data
- Tactile data are correlated temporally and spatially, thus our framework shall be able to handle this structures.

SWT-GP

- Tactile sensor measures pressure when robot touches an object.
- Unlike vision, tactile data don’t suffer from occlusion and continues in nature (one can imagine it as video).
- We propose framework called Sliding Window Temporal Learning with Gaussian process (SWT-GP) to learn data for object classification task.
- SWT-GP is generic algorithm with different possible kernels.

Gaussian Process

- Gaussian Process (GP) is defined as a collection of random variables, any finite number of which have a joint Gaussian distribution:

$$m = \mathbb{E}[f(\boldsymbol{x})]$$
$$k(\boldsymbol{x_i}, \boldsymbol{x_j}) = \mathbb{E}[\left(f(\boldsymbol{x_i}) - m(\boldsymbol{x_i})\right)\left(f(\boldsymbol{x_j}) - m(\boldsymbol{x_j})\right)]$$

where $x_i, x_j \in \mathbb{R}^D$.

- Assumption : $f(x) \sim \mathcal{N}(0, k(\boldsymbol{x_i}, \boldsymbol{x_j}))$

Gaussian Process (Discriminative Model)

- Given test point x_*, we use discriminative model to predict the function distribution as:

$$f(x) \sim \mathcal{N}(f_* \mid \mu_*, \sigma_*^2)$$

Where

$$\mu_* = k(\boldsymbol{x}_*)^T (K + \sigma^2 I_N)^{-1} \, \boldsymbol{y}$$

$$\sigma_*^2 = k(\boldsymbol{x}_*, \boldsymbol{x}_*) - \, k(\boldsymbol{x}_*)^T (K + \sigma^2 I_N)^{-1} \, \boldsymbol{y} k(x_*)$$

and K is known as similarity (a.k.a Gram) matrix. Its computed based on kernel function $k\left(\boldsymbol{x_i}, \boldsymbol{x_j}\right)$.

Kernels

GP can be used with different kernels:

- Squared Exponential Kernel (RBF):

$$k(\boldsymbol{x_i}, \boldsymbol{x_j}) = \exp(-\frac{\left|\left|\boldsymbol{x_i} - \boldsymbol{x_j}\right|\right|^2}{l})$$

- Automatic Relevance Detection (ARD):

$$k(\boldsymbol{x_i}, \boldsymbol{x_j}) = \exp(-\sum \frac{\left|\left|\boldsymbol{x_i} - \boldsymbol{x_j}\right|\right|^2}{l_k})$$

Recursive Kernel

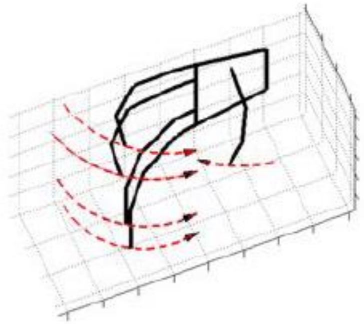
- While ARD kernel handles spatial correlation in data, recursive kernel can pass history data to the current state (similar to RNN):

$$k^t(\boldsymbol{x_i}, \boldsymbol{x_j}) = \exp(-\sum \frac{\left|\left|\boldsymbol{x_i} - \boldsymbol{x_j}\right|\right|^2}{l_k}) \exp(\frac{k^{t-1}(\boldsymbol{x_i}, \boldsymbol{x_j}) - 1}{\rho^2})$$

Tactile Dataset

- Humanoid iCub robot grasps 9 different objects 20 times. Each time hand starts with pre-grasping pose and grasps with specified trajectory.
- The dataset is in open source and can be downloaded by following link: https://bitbucket.org/haroldsoh/otl/downloads/

9 Different object: full and empty soda cans, full, half full and empty bottles, Teddy-bear, monkey toy, book and lotion.



Motion during grasping

Pre-grasping pose

Implementation

- Online learning with SWT-GP is implemented using following algorithm to classify object and improve the accuracy incrementally:

Algorithm 1: Recursive Update of the GP

input : $X \in \{\mathbf{x_1}, ..., \mathbf{x_T}\}$, $Y \in \{y_1, ..., y_T\}$, τ, K_{t-1}, $\dot{K}_{t-1}$
output : $\bar{y}_t$

initialization;
for $t \leftarrow \tau$ **to** T **do**
  $\tilde{X} \leftarrow X_{t:(t+\tau)}$;
  $\tilde{Y} \leftarrow Y_{t:(t+\tau)}$;
  `// update GP with previous kernel value and its gradient`
  $K_{t-1}, \dot{K}_{t-1} \rightarrow$ to GP;
  `// maximize marginal log likelihood, fit GP`
  $K_t, \dot{K}_t = \mathrm{GP}(\tilde{X}, \tilde{Y})$;
  `// predict next test point`
  $\bar{y}_t = \mathrm{GP}(X_{t+1})$
end

Implementation

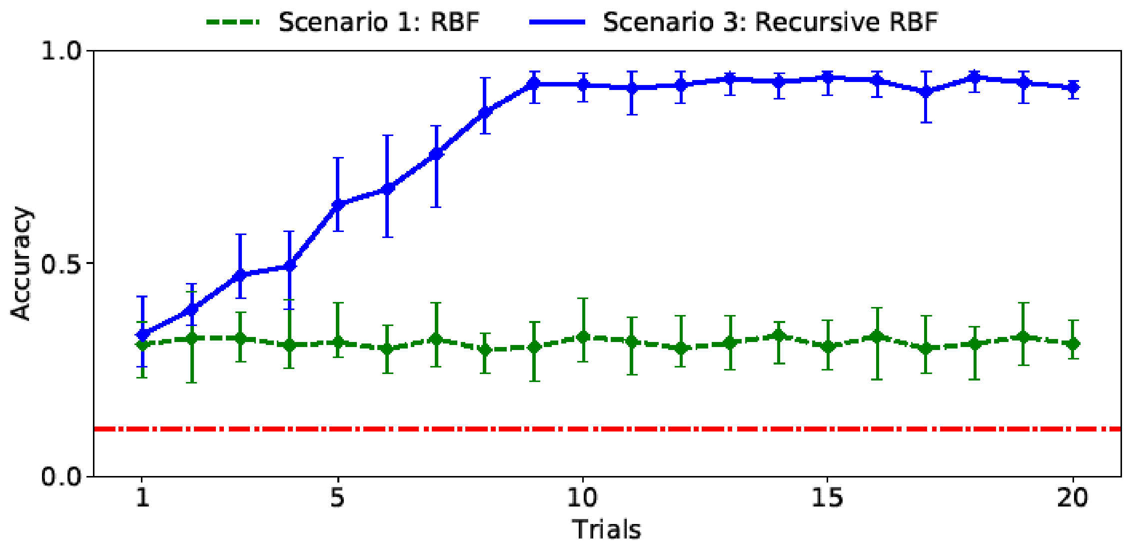
SWT-GP is tested in different scenarios with different kernels:

- **Scenario 1:** GP with Standard RBF kernel
- **Scenario 2:** GP with ARD kernel
- **Scenario 3:** GP with Recursive RBF kernel
- **Scenario 4:** GP with Recursive ARD kernel

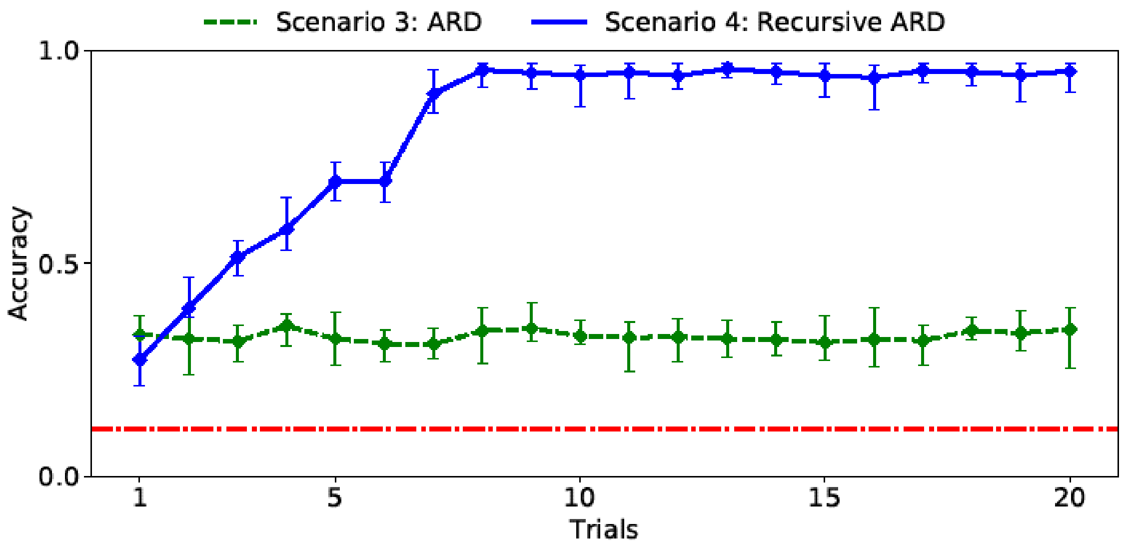
Isotropic kernels

Anisotropic kernels

Results: Accuracy score

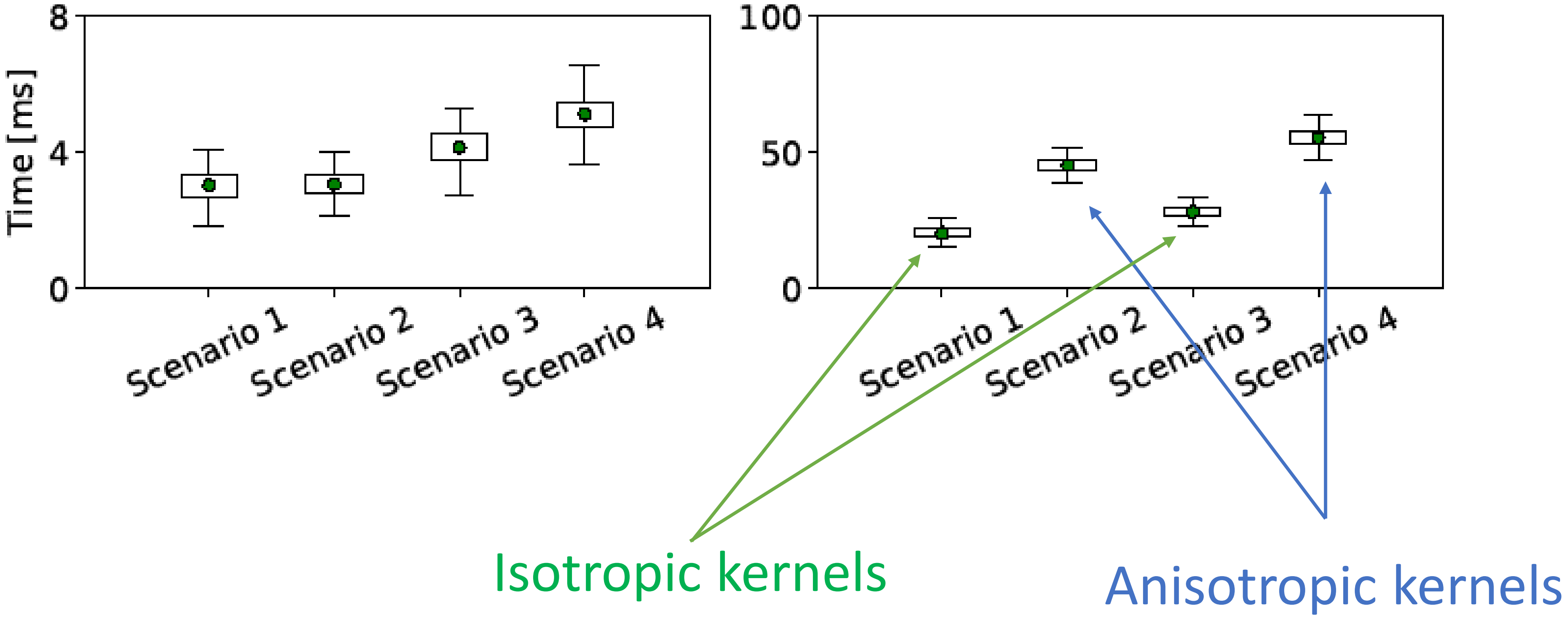


Isotropic kernels



Anisotropic kernels

Results: Execution time



Results: Benchmarking

Table 1: Comparasion of SWT-GP with other Online GP algorithms

Algorithm	Accuracy	Update time, ms	Convergence, trial
SWT-GP RBF	0.332	**19**	-
ARD	0.354	52	-
Recursive RBF	0.961	26	9
Recursive ARD	0.982	57	7
STORK-GP	0.997	40	**4**
OIES-GP	**0.999**	20	**4**

Conclusion

- SWT-GP algorithm is proposed for online learning to classify objects from tactile data.
- The algorithm is tested in 4 different scenarios with different kernels.
- Tactile object classification is feasible using GPs.
- In the future, window size must be analyzed in detail.