Tear Down that Wall: Calculation Reuse Across Inference and Belief Space Planning

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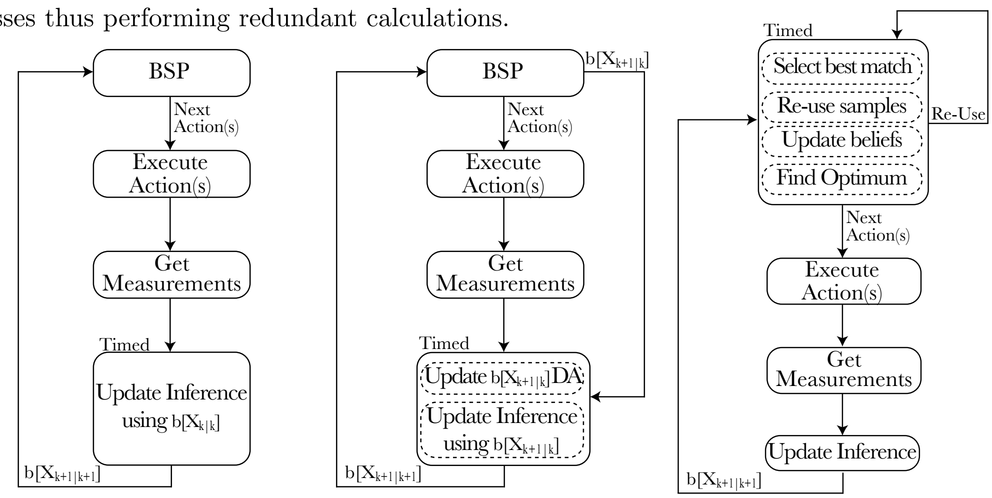
Online operation is desirable in both Autonomous Systems and Artificial Intelligence, hence any computational streamlining is highly beneficial, especially in inference and decision making under uncertainty which impose key processes in both the aforementioned. Decision making under uncertainty and belief space planning are computationally expensive, and even computationally intractable for most realistic scenarios. The inference problem is also computationally expensive when considering high-dimensional state spaces, e.g. SLAM, sensor deployment and numerous similar problems.

Our research vision is that calculations can be re-used between inference and precursory belief space planning (BSP), and within BSP from different time instances. Our key observation is that inference and BSP ,as well as successive BSP sessions, have a built-in inefficiency, and despite the similarities between them, these are treated as separate processes thus performing redundant calculations.



(a) **(b)** **(c)**

Figure 1: High level algorithm for joint inference and BSP presented in a block diagram: (a) presents a standard plan-act-infer framework with Bayesian inference and BSP treated as separate processes; (b) presents our novel approach for inference update using precursory planning. Instead of updating the belief from precursory inference with new information we propose to update the belief from a precursory planning phase; (c) presents our novel approach for incremental expectation for BSP. Instead of calculating a new BSP session from scratch we propose to re-use precursory planning session, by updating the information from inference and through selective re-use of past samples.

Inference Update using Precursory Planning

Only in recent years, the research community has started investigating and exploiting these similarities between inference and decision making.Despite these research efforts, inference and BSP are still being handled as two separate processes. In our work [1, 2] we demonstrated that similarities between inference and decision making paradigms could be utilized in order to save valuable computation time. Updating inference with a precursory planning stage can be considered as a deviation from conventional Bayesian inference. Rather than updating the belief from the previous time instant with new incoming information (e.g. measurements) 1a, we exploit the fact that similar calculations have already been performed within planning, in order to appropriately update the belief in inference more efficiently 1b. We denote this novel approach by Re-Use BSP Inference, or RUBI in short.

As can be seen in Figure 1b, the inference block contains data association (DA) update before the actual inference update, meant to deal with potentially different association between planning and the succeeding inference. Once the DA is consistent, the inference update is being done by updating just the measurement values.

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Incremental BSP

The intractability of the BSP problem originates mainly from the use of expectation in the objective function, $J(\mathcal{U}) = \mathbb{E}_z[\sum_i c_i(b_i, u_{i-1})]$. The objective over a candidate action sequence $\mathcal{U}$, is obtained by calculating the expected value of all possible costs (rewards) c received from following $\mathcal{U}$. Since the cost (reward) function is a function of the belief b and the action led to it u, in practice the objective considers all future beliefs obtained from following $\mathcal{U}$, i.e. all future measurements z. We refer to this general problem as the full solution of BSP, denoted by `X-BSP`, expectation based BSP.

The exponential growth of possible measurements and candidate actions, usually denoted as the *curse of history*, is the key aspect targeted by a lot of research efforts. As in any computational problem, one can either streamline the solution process or change the problem, i.e. take simplifying assumptions or approximations. In strike contrast to the vast amount of research invested in approximating the `X-BSP` problem, only few tried re-using calculations. Although under simplifying assumptions, amongst them Maximum Likelihood (ML), both [3] and [4] re-use computationally expensive calculations during planning. In their work, Chaves and Eustice [3], consider a Gaussian belief under `ML-BSP` in a Bayes tree representation. All candidate action sequences consider a shared location (entrance pose), thus enabling to re-use a lot of the calculations through state ordering constrains. That work enables to efficiently evaluate a single candidate action across multiple time steps, and is conceptually applicable to multiple candidate actions at a single time step. While Kopitkov and Indelman [4], also consider a Gaussian belief under `ML-BSP`, they utilize a factor graph representation of the belief while considering an information theoretic cost. Using an (augmented) determinant lemma, they are able to avert from belief propagation while re-using calculations throughout the planning session. Although they consider calculation re-use within the same planning session, their work can be augmented to consider re-use also between planning sessions.

To the best of our knowledge, in-spite of aforementioned research efforts, calculation re-use has only been done over `ML-BSP`, with restricting assumptions. As for today, `X-BSP` approaches do not re-use calculations between consecutive planning sessions, and regard each planning session for its own. Our *key observation* is that the similarity between two successive planning sessions can be utilized to re-use calculations, thus salvaging valuable computation time. In [5] we provide a novel paradigm for Incremental eXpectation BSP, or `iX-BSP`, which incrementally updates the expectation related calculations in `X-BSP`, by re-using the measurements sampled in a precursory planning session. Instead of re-calculating the planning session each time from scratch, we create it by incrementally updating the precursory session with newly received information, using our previous work on efficient belief update [1,2].

As presented in Figure 1c, instead of re-calculating planning from scratch, we take the relevant segments from precursory planning and update it with information received between the successive planning sessions. First, we locate the predicted measurement closest to the one received in inference, and prune our selection accordingly. We then go over all previously sampled measurements, update their impact over current objective (i.e. importance sampling), which includes updating relevant beliefs while accounting for possibly different DA, and re-sampling.

Our novel paradigms for efficient inference update -`RUBI`, and incremental BSP - `iX-BSP`, provide a substantial reduction in computation time without affecting the solution accuracy. Since they change the approach of the original un-approximated problem, we believe they could be utilized to also reduce computation time of existing approximations.

References

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