DEALING WITH UNCERTAINTY WHEN MANAGING AN EARTH OBSERVATION SATELLITE

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Abstract

The possible presence of clouds is the main origin of uncertainty when managing earth optical observation satellites. Forgetting it can lead to poor results in terms of really achieved photographs. In this paper, we show how a mathematical approach, drawn from the *Markov Decision Process* framework, allows us to define a rational way of taking in account this uncertainty in the daily optimization process.

Keywords : planning, uncertainty, markov decision process

1. Context

At the highest level, managing an earth observation satellite, like *Spot*, consists in choosing the sequence of photographs to be taken. Typically, this choice is made each day for the next day. The set *SA* of the photographs that can be taken the next day (according to the satellite trajectory and the instrument maneuvering ability) is extracted from the current order book. From this set *SA*, one tries to extract a subset *SE* that is feasible (there is no conflict between photographs in *SE*; all the physical satellite constraints are satisfied) and optimal (a gain, usually equal to the sum of the gains associated with each selected photograph, is maximum).

Due to the nature of the problem (a multi-knapsack problem with a large number of capacity constraints, each of them involving only a small number of 0/1 variables*) and to the size of the instances to solve (until several hundreds of 0/1 variables), efficient algorithms[1-2] are needed. Whereas optimal algorithms[3], using a *Branch and Bound* schema, can solve small and medium size instances , only sub-optimal algorithms, using a *Iterative Local Search* schema, can deal with large size instances.

Unfortunately, this daily optimization approach does not take into account the fact that most of the photographs have several other feasibility opportunities after the next day and that the number of remaining feasibility opportunities is highly variable, depending on the deadline associated with each photograph.

Moreover, it takes into account, neither the uncertainty about the realization the next day of the selected photographs (due, with optical instruments, to the possible presence of clouds), nor the uncertainty about the number and the nature of the photographs that will be concurrently added to the order book.

To face this problem, gains associated with each photograph are usually modified in order to favor photographs, that have the smallest number of remaining feasibility opportunities and the highest realization likelihood (good meteorological forecast for the next day). But the way of combining the three criteria (gain, number of remaining feasibility opportunities, meteorological forecast) is not obvious and is generally empirically achieved, without any clear idea of the consequences in terms of really achieved photographs.

* A 0/1 variable is usually associated with each photograph. The value 1 (resp. 0) means that this photograph is selected (resp. not selected).

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2. A rational approach

However, a mathematical approach, drawn from the *Markov Decision Process* (*MDP*) framework[4], currently used in *Decision Theory*, can help us to define a rational way of aggregating those three criteria.

To take into account the presence of several feasibility opportunities for a photograph, it is necessary to consider a global gain criterion over a given horizon rather than a daily gain criterion. A sensible choice consists in considering an horizon that covers all the feasibility opportunities of all the photographs belonging to the current order book. To take into account the presence of uncertainty, it is necessary to consider an expected global gain criterion rather than a global gain criterion.

Using this expected global gain criterion, the strict *MDP* approach leads us to intractable problems, because of the lack of knowledge, even in terms of probability, about the photographs that will be added to the order book and, above all, because of the huge number of states that should be explored by the *Dynamic Programming* algorithm, currently used in the *MDP* framework to compute optimal policies.

Fortunately, thanks to some simplifying assumptions (essentially, no influence of the current decision upon the future expected gains associated with the photographs that either belong to the current order book, or will be added to it), one can establish that the optimal policy (the one that maximizes the expected global gain) consists in selecting each day a set *SE* of photographs that is feasible and maximizes the sum of the weights of the photographs in *SE*, with weights set according the following formula:

$$w(p,\ d_c,\ \pi^*) = g(p) \times p_r(p,\ d_c) \times P_{ef}(p,\ d_c,\ \pi^*) \quad (1)$$

$P_{ef}(p,\ d_c,\ \pi^*)$ being computed by the rule :

$$\begin{aligned}&\textbf{if } RFO(p,\ d_c) = \varnothing \qquad (2)\\&\quad\textbf{then } P_{ef}(p,\ d_c,\ \pi^*) = 1\\&\quad\textbf{else } P_{ef}(p,\ d_c,\ \pi^*) = \\&\qquad\prod_{d \in RFO(p,\ d_c)} [1 - p_r(p,\ d) \times p_s(p,\ d,\ \pi^*)]\end{aligned}$$

where:

- p is a photograph;
- d_c is the current day;
- π^* is the optimal policy;
- $w(p,d,\pi)$ is the weight to be associated to the photograph p, the day d, according to the policy π;
- $g(p)$ is the gain associated with the actual realization of the photograph p;
- $p_r(p,d)$ is the realization probability of the photograph p the day d;
- $P_{ef}(p,\ d,\ \pi)$ is the non-realization probability for the photograph p on the days after d, using the policy π;
- $RFO(p,d)$ is the set of feasibility opportunities of the photograph p, remaining after the day d;
- $p_s(p,d,\pi)$ is the selection probability of the photograph p the day d, using the policy π.

The realization probability of a photograph p the day d can be easily obtained, either from short term meteorological forecasts, or from long term climate statistics.

As for the selection probability of a photograph p the day d, using the policy π, if one assumes that the order book keeps globally stable, at least over a large period, one can consider that it is a function f of p's weight, localization and type, *i.e.*

$$p_s(p,\ d,\ \pi) = f[w(p,\ d,\ \pi),\ l(p),\ t(p)]$$

where $l(p)$ is p's localization and $t(p)$ is p's type. Indeed:

- the higher p's weight is, the higher p's selection probability is;
- the higher the demand in p's area is, the higher the likelihood of conflict with other photographs is and the lower p's selection probability is;
- the more resource consuming p is (example: stereo demands), the lower p's selection probability is.

But, how to fix function f? It seems that a sensible option consists in learning it, in fact in approximating it, either off-line from simulations, or on-line from the observation of the system behavior[5-6]. For example, a multi-layer neural network could be used for that. Whatever the technical option is, note that on-line learning has the advantage to allow the system to adapt itself to mid and long-term changes in the size or the nature of the order book.

As soon as the selection and realization probabilities (p_s and p_r) have been fixed, the recurrent equations 1 and 2 can be used to compute the weight to be associated with a possible photograph: the process starts with the last opportunity ($RFO(p,d) = \varnothing$) and ends with the current one, alternating computations of weights and of selection probabilities.

Note that, as it was foreseeable, equations 1 and 2 favor photographs that:

- have a high associated gain;
- are subject to a good meteorological forecast for the next day;
- have a small number of remaining feasibility opportunities;
- are subject to bad meteorological forecasts for the days associated with these remaining feasibility opportunities;
- are localized in areas in great demand;
- are very resource consuming.

3. Conclusion

As a conclusion, thanks to some simplifications, an *MDP*-like approach provides us with a rational way of dealing with uncertainty when managing an earth observation satellite. The next step of this work would consist in fixing the learning process of the selection probability and in carrying out simulations in order to measure the actual gain in terms of achieved photographs.

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