Dynamic ranking algorithm for landing site selection

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Abstract

Landing on planets is always a challenging task due to the distance, communication delays, and hostile environments found. In this paper we present a dynamic ranking algorithm, based on a hybrid aggregation operator, for selecting the best site for landing. The proposed algorithm uses feedback historical information from previous iterations to ensure a reinforcement behavior in the decision process.

Keywords: aggregation operators, dynamic ranking algorithm, hazard maps.

1 Introduction

Past planetary lander missions tended to focus on pre-qualified landing sites, which implied a smooth terrain with little risk and few geologic features [4]. Landing on planets is always a challenging task due to the distance and hostile environments found. Improving the landing site selection process implies greater onboard autonomy, due to communication time delays and data volume involved.

ASTRIUM Space Transportation has been consistently improving the hazard avoidance techniques for on-board piloting autonomy [2, 4] (denoted piloting function). Hazard avoidance includes three separate critical functions [2, 4]: hazard mapping that estimates ground features based on an imaging sensor data (camera or Lidar); site selection that chooses a suitable landing site based on available hazard maps, mission, propulsion and guidance constraints; and a robust guidance to reach the selected target.

In this work our inputs are hazard maps of dimensions 512x512 pixels that provide assessments of terrain features and trajectory constraints. From these maps we have to select the best site (pixel x, y in the aggregated map).

Since the selection of a suitable landing site is a critical task for any planetary mission success, the motivation for this work is to build a fuzzy multiple attribute decision-making process to select the best site. Specifically, in this paper we focus on the second step of a fuzzy multiple attribute (or criteria) decision-making process, the ranking of alternatives with respect to the global aggregated degree of satisfaction [6].For this purpose we present a dynamic algorithm for landing site ranking, taking into account past historical data from previous iterations, during the piloting function.

The proposed dynamic ranking algorithm uses a hybrid aggregation operator, based on ideas from the uninorm aggregation operator [3, 9], for combining past and present data because it ensures a full reinforcement behavior [1, 10]. If we encounter a collection of high values we want that the resulting aggregation value to be more positive than any of the individual values. On the other hand, if we encounter a collection of low values we want that resulting aggregation value to be more discriminative than any individual values. The first concept is called upward reinforcement and the second concept is called downward reinforcement. Most aggregation/ranking methods are only either

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upward (e.g. Hamacher and Dubois & Prade union operators [5, 11]) or downward methods (e.g. Hamacher and Dubois & Prade intersection operators [5, 11]). When we combine these two concepts we achieve what is called full reinforcement behavior [8], and our hybrid operator and the uninorm operator belong to this category.

This paper is organized as follows. This first section presents the context for the development of the dynamic ranking algorithm. The second section presents a brief overview of the aggregation operators used in this work. The third section presents the proposed dynamic ranking algorithm. The fourth section presents an example on how the algorithm works and finally the fifth section presents the conclusions.

2 Aggregation operators

In this section we first present a brief overview of the uninorm operator [9], which is the basis of our hybrid operator, for the proposed dynamic ranking algorithm. Second, we discuss the hybrid reinforcement operator that is suitable for use in our dynamic algorithm.

2.1 Uninorm operator & hybrid reinforcement operator

T-norms and S-norms (or t-conorms) play an important role in fuzzy logic [1, 11] in generalizing the “And” and “Or” operators, but neither allows a compensatory behavior. For instance, t-norms do not allow low values to be compensated by high values and s-norms do not allow high values to be compensated by low values [1].

The uninorm aggregation operator is the result of the unification of both t-norm and s-norms, studied and presented by Yager, Fodor and Rybalov [3]. One of the main characteristics of this operator is the consideration of a neutral element, anywhere in the interval]0, 1[.

Definition (Yager and Rybalov [9]): A Uninorm operator R is a mapping $R:[0,1]\times[0,1]\rightarrow[0,1]$

having the following properties:

(1) Commutativity $R(a,b)=R(a,b)$;

(2) Monotonicity (increasing)

$R(a,b)\le R(c,d)$, if $a\le c$ and $b\le d$;

(3) Associativity $R(a,R(b,c))=R(R(a,b),c)$;

(4) There exists some element $e\in[0,1]$, called the neutral element, such that for all $e\in[0,1]$, $R(a,e)=a$.

Another important characteristic of the uninorm operator is its full-reinforcement behavior [5]. This means that if we have a collection of high values we want the resulting aggregation value to be more positive than any of the individual values. On the other hand, if we encounter a collection of low values we want the resulting aggregation value to be more discriminative than any of the individual values.

2.2. Hybrid reinforcement operator

For our case study we need an aggregation operator with the full reinforcement characteristics of uninorm operator, but combined with an averaging compensatory operator, such as the OWA[7], in the interval $]0,\eta[\times]\eta,1[\cup]\eta,1[\times]0,\eta[$. This is the interval outside the solution space of t-norms and s-norms, since these are bounded by the neutral element η.

For this purpose we present a hybrid reinforcement operator U, which is a mapping $[0,1]\times[0,1]\rightarrow[0,1]$,

$$U(x,y)=\begin{cases}\eta.T(\frac{x}{\eta},\frac{y}{\eta}), & \text{for } x\le\eta \text{ and } y\le\eta\\ \eta+(1-\eta).S(\frac{x-\eta}{1-\eta},\frac{y-\eta}{1-\eta}), & \text{for } x\ge\eta \text{ and } y\ge\eta\\ \mathrm{OWA}(x,y), & \text{elsewhere}\end{cases}$$

where:

η is a neutral element;

T represents any t-norm intersection operator[5];

S represents any s-norm union operator [5];

OWA represents Yager´s OWA operator [7].

As we can observe this operator does not fulfill all properties of uninorm operators because it does not satisfy the associativity condition. The reason for this hybrid algorithm is the need for an operator with an averaging compensatory nature, outside the t-norms and s-norms interval. In addition, since each iteration just aggregates historical and rating values there are no associative problems. All other properties of uninorm operators are satisfied, by this hybrid version, on $[0,1]\times[0,1]$.

3. Dynamic ranking algorithm

The dynamic ranking algorithm discussed in this section assumes that we already determined the aggregated rating for each possible alternative site of iteration *k*, as can be observed in Figure 1.

Our dynamic ranking algorithm uses the hybrid reinforcement operator U, defined in section 2.2, for combining the historical information (H_{n-1}) and current rating value (R_n). We use this operator for four reasons: a) it has a full reinforcement capability; b) it has a full compensatory nature; c) takes into consideration the order of elements; d) using the Hamacher operators [11] for T-norm and S-norm we achieve a synergy between arguments. This combination of operators is what we are looking for in our adaptable and dynamic decision process based on historical data.

The ranking process at iteration *n*, is computed using the following rationale:

- If a site belongs to the historic set it means that at earlier iterations it had good rating values. Hence, if the current iteration has a high rating value (i.e. its value is greater than the neutral element) we want to increase its value, otherwise we want to penalize its value.
- If a site does not belong to the historic set we do not have any past information about the site. Hence, we give the benefit of doubt, i.e., in the current iteration we give the same value as the rating value.

Our dynamic ranking algorithm works as follows. Consider h_{n-1} (historic rating value of a site S_{ij} that belongs to historic H_{n-1}) and r_n (current rating value of the same site S_{ij}). The dynamic ranking algorithm of site $S_{ij,}$ at iteration *n*, is computed as follows:

$$DR(H_{n-1},R_n)=\begin{cases}\eta.TH(\frac{H_{n-1}}{\eta},\frac{R_n}{\eta}), \\ \quad \text{for } H_{n-1}\le\eta \text{ and } R_n\le\eta \\ \eta+(1-\eta).SH(\frac{H_{n-1}-\eta}{1-\eta},\frac{R_n-\eta}{1-\eta}), \\ \quad \text{for } H_{n-1}\ge\eta \text{ and } R_n\ge\eta \\ \text{OWA}(H_{n-1},R_n), \text{ elsewhere}\end{cases}$$

Where the neutral element η is a parameter which influences the quantity of upward or downward reinforcement operations. In our case we use quantiles for neutral element because with a high quantile we ensure the majority of values fall before the bounded quantile value, hence more downward reinforcement operations. Using a lower quantile we ensure more upward reinforcement operations in the final aggregation.

For S-norm and T-norm (SH, TH) we use the following Hamacher operator formulas [5]:

$$SH_\alpha(a,b)=\frac{a+b-(2-\alpha)*a*b}{1-(1-\alpha)*a*b},$$
$$\text{where } \alpha\in[0;+\infty[\text{ and a,b}\in[0;1]$$
$$TH_\alpha(a,b)=\frac{a*b}{\alpha+(1-\alpha)(a+b-a*b)},$$
$$\text{where } \alpha\in[0;+\infty[\text{ and a,b}\in[0;1]$$

In our case study we use a low value for parameter α because we want to benefit or penalize the rating values smoothly instead of using aggressive aggregation behaviour.

For the OWA aggregation operator we use the following formulation:

$$OWA(a,b)=w_1\times\max(a,b)+w_2\times\min(a,b)$$
$$\text{where } w_1+w_2=1 \quad \text{and} \quad \text{a,b}\in[0;1]$$

The weights for the OWA aggregation operator (w_1 and w_2) will have in consideration that giving more weight to lower values will decrease the aggregation value; this is what we are looking to avoid selecting sites with lower rating values.

Finally, we proceed to order the ranked aggregated values decreasingly. From this ordered list we select the next list of historic values. At each iteration *n* we select *k* best ranked sites, and, depending on the altitude from the planet the historical set size varies. For example, for an altitude of around 1000 meters from the soil we would select several hundred sites, while for lower altitudes we select tenth's. Hence, the historical data set for the next iteration will contain *k* possible sites with good chances of being selected again.

With this ranking procedure, it can happen that the best choice of alternative is not the highest regarding its rating value, in the respective iteration. This situation is due to the use of historical feedback information and the behavior of the hybrid reinforcement operator in the computation of the dynamic ranking algorithm. We want to select sites that proved to be good for a certain period of time!

In summary, the general decision making process, including the dynamic ranking algorithm is depicted in Figure 1.

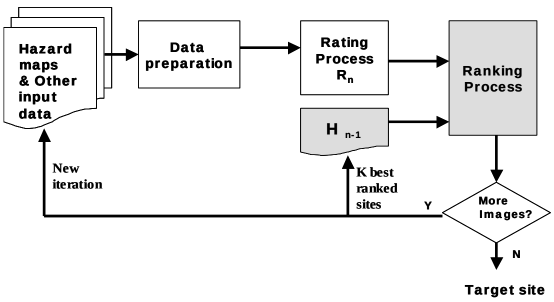

Figure 1 - Site Selection Decision Process

4 Illustrative case

The goal of this case study is to provide the trajectory planning function with an adequate target-landing site. The site adequacy is evaluated with respect to a set of requirements: (1) the site should be safe in terms of maximum local slope, light level and terrain roughness; (2) the site should be reachable with the available fuel; (3) the site should be visible from the camera along the piloting function.

The different hazard maps quantify each requirement and are given as inputs for our decision process (see Figure 1).

The algorithm parameters were tuned to get a coherent behavior. The neutral element η was set to a high quantile of R_n to obtain a small subset with high classifications. Then, we determined the α parameter for both Hamacher operators (SH and TH equations), and weights used for the OWA aggregation operator. In this paper we do not provide the exact parameter values for confidentiality reasons.

After the rating process (see Figure 1), which aggregates all information provided in the hazard maps, we apply the dynamic algorithm (DR) to combine current rating values with past historic values. If there are more iterations (hazard maps) we update the historic set with the top best sites of the current iteration and the process repeats itself.

Considering an illustrative example with only 12 iterations and an historic size of 5 elements, the final results are now discussed.

Table 1, depicts the "best" alternative site, selected in each of the 12 iterations. Each row includes the 2D coordinates (considering image map size 512x512), current rating value (r_n), historic value (h_{n-1}) and the obtained dynamic ranking value (DR_n).

Table 1 – Best result obtained for each iteration.

Iter.	2D coord (meters)	R_n	H_{n-1}	DR_n
1	(244,243)	0.790	-	0.790
2	(220,255)	0.789	0.77	0.824
3	(227,248)	0.773	0.814	0.854
4	(224,248)	0.774	0.849	0.88
5	(224,249)	0.719	0.88	0.887
6	(224,249)	0.775	0.887	0.908
7	(224,249)	0.749	0.908	0.92
8	(224,249)	0.78	0.92	0.937
9	(224,249)	0.77	0.937	0.948
10	(224,249)	0.762	0.948	0.955
11	(224,249)	0.782	0.955	0.963
12	(228,256)	0.766	0.898	0.912

In Figure 2 we can observe the best 5 results in the final landing area image. The "best" ranked site of the last 12^{th} iteration is marked with 1 and the next 4 best are also highlighted.

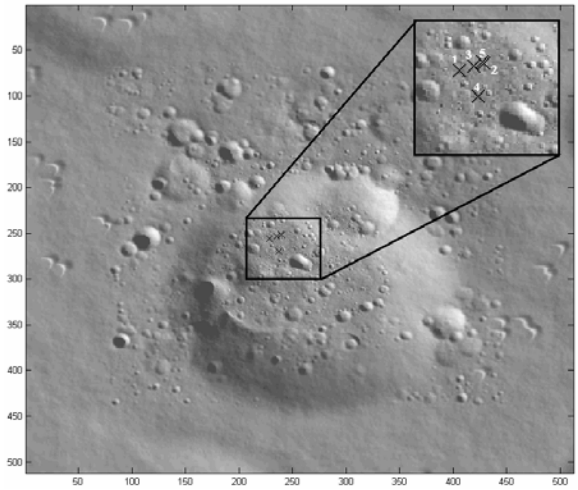

Figure 2 – Image of landing area.

The details of the 5 best results, depicted in Figure 2, are presented in Table 2.

Table 2 – 5 best ranked results after 12 iterations.

Iter_12

R_n	H_{n-1}	DR_n	2D coord	
0.7659	0.8981	0.912	228	256
0.742	0.8911	0.8975	240	252
0.7599	0.8757	0.8904	235	253
0.7874	0.8343	0.8701	237	270
0.7437	0.8428	0.8533	239	251

Observing Table 2 we see that the results are ordered decreasingly and the "best" site, i.e. the site to be selected for re-targeting, corresponds to the last one depicted in Table 1. The "best" site to be selected clearly shows that it is well rated (r=0.7659), its historical value is the highest (h=0.8981) and the final result is the "best" in the list (DR_n=0.912).

It is interesting to note that although the result in line 4 (r=0.7874) has a better rating than the "best" one, since its historical value is low the final ranking value (DR_n=0.8701) is substantially lower that the one achieved by the "best" site.

Another interesting aspect of the ranking process with the dynamic algorithm is that most results kind of "converge" to the same region (see Figure 2) because of past historical information from other iterations.

In summary, the "best" site result shows how the dynamic ranking algorithm reinforces the final classification with a good historical value.

5 Conclusions

This paper introduced a dynamic ranking algorithm for selecting sites for landing, which combines current sites ratings with historical information. The algorithm is applied to each iteration of the piloting function and the best-ranked are selected for historic set of next iteration. At the end the best site is chosen as target landing.

The dynamic algorithm uses a hybrid aggregation operator, which includes Hamacher intersection and union operators, as well as the averaging compensatory OWA operator. As future work we plan to compare the results obtained using the selected operators with other averaging compensatory operators, other S-norms and T-norms operators, as well as other full reinforcement operators.

An illustrative example with 12 iterations was used to discuss the site selection decision process.

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References

1. Detyniecki, -.m. *Fundamentals on Aggregation Operators*. in *AGOP*. 2001. Asturias.
2. Devouassoux, Y., S. Reynaud, G. Jonniaux, R.A. Ribeiro, and T.C. Pais. *Hazard avoidance developments for planetary exploration*. in *7th International ESA Conference on Guidance, Navigation & Control Systems*. 2008.
3. Fodor, J.C., R.R. Yager, and A. Rybalov, *Structure of uninorms.* International Journal of Uncertainty Fuzziness and Knowledge-Based Systems, 1997. **5**(4): p. 411-427.
4. Jean-Marius, T. and S.E. Strandmoe, *Integrated vision and navigation for a planetary lander.* 1998.

5. Klir, G.J. and T.A. Folger, *Fuzzy Sets, Uncertainty, and information*. 1988: Prentice Hall.
6. Ribeiro, R.A., *Fuzzy multiple attribute decision making: A review and new preference elicitation techniques.* Fuzzy Sets and Systems Fuzzy Multiple Criteria Decision Making, 1996. **78**(2): p. 155-181.
7. Yager, R.R., *Ordered weighted averaging aggregation operators in multi-criteria decision making.* IEEE trans. On Systems, Man and Cybernetics, 1988. **18**(1): p. 636-643.
8. Yager, R.R., *Misrepresentations and challenges: A response to Elkan.* IEEE Expert: Intelligent Systems and Their Applications, 1994. **9**(4): p. 41-42.
9. Yager, R.R. and A. Rybalov, *Uninorm aggregation operators.* Fuzzy Sets and Systems, 1996. **80**(1): p. 111-120.
10. Yager, R.R. and A. Rybalov, *Full Reinforcement Operators in Aggregation Techniques.* IEEE Systems, Man, and Cybernetics, Part B, 1998. **28**(6).
11. Zimmermann, H.J., *Fuzzy Set Theory*. 3rd ed. 1996: Kluwer Academic Publishers.