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Generic Prioritization Framework For Target Selection And Instrument Usage For Reconnaissance Mission Autonomy

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***Abstract*—A generic prioritization framework is introduced for addressing the problem of automated prioritization of target selection and instrument usage, applicable to Earth and Space reconnaissance missions. The framework is based on the assumptions that clustering of preliminary data for identified targets within an operational area has occurred and that the clustering quality can be expressed as an objective function. Target prioritization then means to rank targets according to their probability of changing the objective function value upon close reexamination. The formalism for calculating these probabilities and the probabilities for instruments aboard a science craft to contribute to this change of the objective function value is introduced.**

I. Introduction

A fundamentally new scientific mission concept for (remote) planetary surface and subsurface reconnaissance recently has been devised [1]-[4] that is aimed at replacing the engineering and safety constrained mission designs of the past. Traditional missions have performed local, ground-level reconnaissance through rovers and immobile landers, or global mapping performed by an orbiter. The former is safety and engineering constrained, affording limited detailed reconnaissance of a single site at the expense of a regional understanding, while the latter returns immense datasets, often overlooking detailed information of local and regional significance.

A "tier-scalable" paradigm integrates multi-tier (orbit⇔atmosphere⇔surface/subsurface) and multi-agent (orbiter(s)⇔blimps⇔rovers, landers, drill rigs, sensor grids) hierarchical mission architectures [1]-[4], not only introducing mission redundancy and safety, but enabling and optimizing intelligent, unconstrained, and distributed science-driven exploration.

To support such tier-scalable reconnaissance mission architectures, a high level of operation autonomy is required. One important aspect of such operation autonomy is to automatically prioritize targets for close-up reexamination (e.g., with ground-agents) based on preliminary (coarse) data, gathered by, for example, space- and airborne sensor platforms.

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Multiple prioritization scenarios can be conceived to evaluate the (scientific) importance of individual targets or combinations of targets to be revisited/reexamined more closely during reconnaissance missions (e.g., by a field rover on Mars), which differ in their respective level of complexity.

A. Simple Feature-based Prioritization

Target data, for example in form of feature vectors (see I.B), gathered by a science craft about an operational area (e.g., Mars rover traversing the planetary surface) can be prioritized for downlink in multiple ways such as: (a) by simply comparing the extracted feature data for all the identified targets within the operational area, for example, via direct comparison, Hamming distance, or overlap (i.e., dot product) between feature vectors; (b) by calculating the average feature values for all the identified targets within the operational area together with their standard variations: a relatively small standard variation denotes little variation among the identified targets, suggesting a rather low to medium priority for reexamination, whereas a relatively large standard variation would indicate a certain amount of diversity among the identified targets, suggesting a relatively high priority for reexamination.

B. Feature-Clustering-based Prioritization

Clustering algorithms are dependent on the presence of features, which distinguish among the data. These features can be mathematically represented as feature vectors. For a science craft (e.g., planetary rover) traversing an operational area (e.g., a planetary surface), for example, the extracted feature vectors of the targets encountered can provide the basis for mapping the operational area. The target feature vectors could be obtained through automated feature-extraction software packages, such as with the *Automated Geologic Field Analyzer (AGFA)* [5].

The clustering of the extracted feature vectors can be accomplished by applying standard clustering algorithms such as K-means [6], EM for mixture models [7], and hierarchical clustering [8]. Hereby each encountered target would be assigned a normalized membership value with respect to each occurring cluster. This type of labeling could be used to prioritize a target or sets of targets for close-up reexamination or target information for downlink: for example, an image containing an outlier would be given a relatively high downlink priority. In contrast an image containing a target that belongs to one of the pre-determined clusters with high confidence would be assigned a relatively low to medium downlink priority, provided that sufficient images of this target type are scheduled for downlink or have been downlinked before.

C. Prioritization via Context-based Clustering

A more complex scenario could utilize clustering algorithms in conjunction with special-purpose models to not only cluster the feature information of the encountered targets within an operational area, but to organize the encountered targets into clusters and these clusters into super-clusters, leading to a more global picture of the operational area. These special-purpose models are specifically tailored to the nature of the operational area and the data types gathered within. An example for such a special-purpose model and its associated clustering algorithm for mutually constraining heterogeneous feature spaces is the "Rock-Patch-Facies-Deposit Model" [9], applicable to geologic planetary surface exploration. Such a model may lead to a more global picture such as geologic boundaries of a geologic field site/traverse area, which ultimately could contribute to the understanding of the geologic history of a region.

II. Prioritization Framework For *Single* Targets

For the purpose of deriving a prioritization framework for single targets, previously identified at a coarse level in an operational area, to be revisited more closely for potential "knowledge gain" about the operational area, it is assumed in the following that preliminary feature/reconnaissance data about the targets have been gathered and pre-clustering using general purpose clustering algorithms (e.g., [6]-[8], see I.B) or clustering algorithms associated with special-purpose models (e.g., [9], see I.C) has occurred.

The quality of the data clustering can be expressed in form of an objective function E and can be formulated in more general terms as follows:

$$E(t) = \sum_{k=1}^{K}\sum_{i=1}^{N} M_{ki}(t)\left(\left\|\mathbf{c}_i(t) - \mathbf{cc}_k(t)\right\|^2 - \mu\right), \tag{1}$$

with $M_{ki}(t)$ being the membership value of a target $i\in\{1,\ldots,N\}$ with respect to cluster k at time t, with $0\leq M_{ki}(t)\leq 1$ and the sum of all M_{ki} over all clusters $k\in\{1,\ldots,K\}$ being normalized to 1, $\boldsymbol{c}_i(t)$ the current feature vector of target i at time t, $\boldsymbol{cc}_k(t)$ the current cluster center vector in feature space (see definition below) of cluster k at time t, and μ a constant reward/penalty term.

The value of the objective function E is a measure for the "knowledge" about the targets within an operational area and the area itself: a "knowledge gain" is defined as being synonymous with lowering the objective function value. Target prioritization in this context means to rank individual targets or sets of targets according to their probability to increase the "knowledge", i.e., to lower the objective function E, upon close reexamination. Using (1), a change in the objective function E can be expressed as a difference between the objective function at a time t-1, i.e., clustering of data obtained during a first preliminary scan of and data gathering within the operational area and identified targets therein, and the objective function at a (future) time t, i.e., clustering of data based on "hypothetical probing" of individual targets within the operational area:

$$\begin{aligned}\Delta E &= E(t) - E(t-1)\\ &= \sum_{k=1}^{K}\sum_{i=1}^{N} M_{ki}(t)\left(\left\|\mathbf{c}_i(t) - \mathbf{cc}_k(t)\right\|^2 - \mu\right)\\ &\quad - \sum_{k=1}^{K}\sum_{i=1}^{N} M_{ki}(t-1)\left(\left\|\mathbf{c}_i(t-1) - \mathbf{cc}_k(t-1)\right\|^2 - \mu\right)\\ &= \sum_{k,i}\begin{bmatrix} M_{ki}(t)\left\|\mathbf{c}_i(t) - \mathbf{cc}_k(t)\right\|^2 \\ -M_{ki}(t-1)\left\|\mathbf{c}_i(t-1) - \mathbf{cc}_k(t-1)\right\|^2 \end{bmatrix},\end{aligned} \tag{2}$$

with $\boldsymbol{cc}_k$ calculated as follows:

$$\mathbf{cc}_k := \frac{\sum_{i=1}^{N}\theta_{ki}\mathbf{c}_i}{\sum_{i=1}^{N}\theta_{ki}} \text{ with } \theta_{ki} := \begin{cases} 1 \text{ if } M_{ki} = \max\limits_{m\in\{1,\ldots,K\}}\{M_{mi}\} \\ 0 \text{ else}\end{cases}.$$

Alternate, differently weighted schemes for the calculation of the K cluster center vectors $\boldsymbol{cc}_k$ can be applied.

The conditions for the "hypothetical probing" for a particular target $i^*\in\{1,\ldots,N\}$ and cluster $k^*\in\{1,\ldots,K\}$ mentioned above are mathematically introduced as follows:

$$M_{ki^*}(t-1) = \delta_{k,k_{\max}}, M_{ki^*}(t) = \delta_{k,k^*}, \text{ and } \mathbf{c}_{i^*}(t) = \mathbf{cc}_{k^*}(t-1),$$

with δ being the Kronecker-delta-function. The first two conditions mean that for time t-1 the maximum (strongest) cluster membership for a particular target i^* is set to 1 (i.e., absolute membership), and for time t the membership with a particular cluster k^* is hypothetically set to 1 as part of the "hypothetical probing". All other cluster memberships of that particular target i^* for time t-1 and t are set to 0. The third condition assumes that the feature vector $\boldsymbol{c}_{i^*}(t)$ of the particular target i^* upon reexamination is hypothetically set to be the cluster-center vector of the particular cluster k^* at time t-1, $\boldsymbol{cc}_{k^*}(t-1)$, of the preliminary scan, into which it is placed with absolute cluster membership as part of the "hypothetical probing" at time t. It should be noted that there may be other approaches to assigning a new feature vector to target i^* at time t. The advantage of the above method is that only "known" data are used (i.e., cluster information at time t-1) and therefore no additional assumptions or instrument measurements are needed.

These mathematical conditions for the "hypothetical probing" inserted in (2) yield the following change in the objective function for a particular target i^* and cluster k^*:

$$\begin{aligned}\Delta E(k^*,i^*) &= \sum_{k,i\neq i^*}\begin{bmatrix} M_{ki}(t)\left\|\mathbf{c}_i(t) - \underbrace{\mathbf{cc}_k(t)}_{\text{modified}}\right\|^2 \\ -M_{ki}(t-1)\left\|\mathbf{c}_i(t-1) - \mathbf{cc}_k(t-1)\right\|^2 \end{bmatrix}\\ &\quad + \underbrace{M_{k^*i^*}(t)}_{\text{modified}}\left\|\underbrace{\mathbf{c}_{i^*}(t)}_{\text{modified}} - \underbrace{\mathbf{cc}_{k^*}(t)}_{\text{modified}}\right\|^2\\ &\quad - \underbrace{M_{k_{\max}i^*}(t-1)}_{\text{modified}}\left\|\mathbf{c}_{i^*}(t-1) - \mathbf{cc}_{k_{\max}}(t-1)\right\|^2.\end{aligned}$$

For a particular target $i^* \in \{1,\ldots,N\}$ and cluster $k^* \in \{1,\ldots,K\}$ the following function can be defined:

$$\varphi_1\left(\Delta E\left(k^*,i^*\right)\right) := \begin{cases} 1 \text{ if } \Delta E\left(k^*,i^*\right) < 0 \\ 0 \text{ else} \end{cases}. \quad (3)$$

With the above definition (3) a probability $P(i^*)$ for a particular target i^* to lower the objective function E upon changing its current cluster membership ($M_{ki^*}(t-1)=\delta_{k,kmax}$ and $M_{ki^*}(t)=\delta_{k,k^*}$) as well as its current feature vector ($\mathbf{c}_{i^*}(t)=\mathbf{cc}_{k^*}(t-1)$) can be formulated as follows:

$$P\left(i^*\right) = \frac{\sum_k \varphi_1\left(\Delta E\left(k,i^*\right)\right)}{K},$$

or formulated as a weighted probability:

$$P\left(i^*\right) = \frac{\sum_k \varphi_1\left(\Delta E\left(k,i^*\right)\right)\left|\Delta E\left(k,i^*\right)\right|}{\sum_k \left|\Delta E\left(k,i^*\right)\right|}.$$

It is worthwhile noting that the computational effort for calculating the probabilities $P(i)$ for all N targets is $O(N \cdot K)$.

III. Prioritization Framework For *Multiple* Targets

The introduced formalism in II can easily be generalized to a multi-target scenario. For simplicity but without loss of generality the expansion for a set of two targets is shown in the following.

The change in the objective function E for two targets i^* and $i^\#$, and two clusters k^* and $k^\#$, respectively, reads:

$$\begin{aligned}\Delta E\left(k^*,i^*;k^\#,i^\#\right) = \sum_{k,i\neq i^*,i^\#} &\left[\begin{matrix} M_{ki}(t)\left\|\mathbf{c}_i(t) - \underbrace{\mathbf{cc}_k(t)}_{\text{modified}}\right\|^2 \\ -M_{ki}(t-1)\left\|\mathbf{c}_i(t-1) - \mathbf{cc}_k(t-1)\right\|^2 \end{matrix}\right] \\ &+\underbrace{M_{k^*i^*}(t)}_{\text{modified}}\left\|\underbrace{\mathbf{c}_{i^*}(t)}_{\text{modified}} - \underbrace{\mathbf{cc}_{k^*}(t)}_{\text{modified}}\right\|^2 \\ &-\underbrace{M_{k_{\max\ \text{for}\ i^*}i^*}(t-1)}_{\text{modified}}\left\|\mathbf{c}_{i^*}(t-1) - \mathbf{cc}_{k_{\max\ \text{for}\ i^*}}(t-1)\right\|^2 \\ &+\underbrace{M_{k^\#i^\#}(t)}_{\text{modified}}\left\|\underbrace{\mathbf{c}_{i^\#}(t)}_{\text{modified}} - \underbrace{\mathbf{cc}_{k^\#}(t)}_{\text{modified}}\right\|^2 \\ &-\underbrace{M_{k_{\max\ \text{for}\ i\#}i^\#}(t-1)}_{\text{modified}}\left\|\mathbf{c}_{i^\#}(t-1) - \mathbf{cc}_{k_{\max\ \text{for}\ i\#}}(t-1)\right\|^2.\end{aligned}$$

Akin to (3) the following function can be defined:

$$\varphi_2\left(\Delta E\left(k^*,i^*;k^\#,i^\#\right)\right) := \begin{cases} 1 \text{ if } \Delta E\left(k^*,i^*;k^\#,i^\#\right) < 0 \\ 0 \text{ else} \end{cases}. \quad (4)$$

With the above definition (4) a probability $P(i^*,i^\#)$ for a particular set of two targets $(i^*,i^\#)$ to lower the objective function E upon change of their respective current cluster memberships ($M_{ki^*}(t-1)=\delta_{k,kmax\_for\_i^*}$ and $M_{ki^*}(t)=\delta_{k,k^*}$, and $M_{ki\#}(t-1)=\delta_{k,kmax\_for\_i\#}$ and $M_{ki\#}(t)=\delta_{k,k\#}$) and their respective current feature vectors ($\mathbf{c}_{i^*}(t)=\mathbf{cc}_{k^*}(t-1)$ and $\mathbf{c}_{i\#}(t)=\mathbf{cc}_{k\#}(t-1)$) can be formulated as follows:

$$P\left(i^*,i^\#\right) = \frac{\sum_{k^*}\sum_{k^\#} \varphi_2\left(\Delta E\left(k^*,i^*;k^\#,i^\#\right)\right)}{K^2},$$

or formulated as a weighted probability:

$$P\left(i^*,i^\#\right) = \frac{\sum_{k^*}\sum_{k^\#} \varphi_2\left(\Delta E\left(k^*,i^*;k^\#,i^\#\right)\right)\left|\Delta E\left(k^*,i^*;k^\#,i^\#\right)\right|}{\sum_{k^*}\sum_{k^\#}\left|\Delta E\left(k^*,i^*;k^\#,i^\#\right)\right|}.$$

It should be pointed out that the computational effort for calculating all $N \cdot (N-1)/2$ probabilities $P(i^*,i^\#)$ (with $i^* \neq i^\#$) is now $O((N \cdot K)^2)$. The generalization of the above prioritization framework to sets of more than two targets is treated accordingly.

IV. Prioritization Framework For Instrument Usage

Similar to the target prioritization frameworks introduced in II and III, a mathematical framework for an instrument prioritization scenario can be formulated. Without restriction of generality, only two instruments I_A and I_B, operating on a single target i^*, are considered in the following.

Instrument I_A (e.g., an optical camera onboard a satellite platform) is responsible for measurements stored in the first f components of the feature vector $\mathbf{c}_{i^*}(t)$ for a particular target i^*. Instrument I_B (e.g., a spectral imager onboard the satellite platform) is responsible for measurements stored in the remaining *(CDIM-f)* components of the same feature vector $\mathbf{c}_{i^*}(t)$ for target i^*, where $CDIM=dimension(\mathbf{c}_{i^*})$.

The respective probability for each instrument to contribute to a possible "knowledge gain" (defined as lowering the objective function E, see II), if used in a hypothetical measurement, is calculated for each instrument individually as follows:

$$P\left(i^*\right) = \frac{\sum_k \varphi_1\left(\Delta E\left(k,i^*\right)\right)}{K},$$

or formulated as a weighted probability:

$$P\left(i^*\right) = \frac{\sum_k \varphi_1\left(\Delta E\left(k,i^*\right)\right)\left|\Delta E\left(k,i^*\right)\right|}{\sum_k \left|\Delta E\left(k,i^*\right)\right|},$$

but this time with a *partially updated* feature vector $\mathbf{c}_{i^*}(t)$ according to the instrument used, meaning: $\mathbf{c}_{i^*}(t)=\mathbf{cc}_{k^*}(t-1)$ for feature vector components $1,\ldots,f$ with feature vector components $f+1,\ldots,CDIM$ unchanged (i.e., $\mathbf{c}_{i^*}(t)=\mathbf{c}_{i^*}(t-1)$) for instrument I_A, and $\mathbf{c}_{i^*}(t)=\mathbf{cc}_{k^*}(t-1)$ for feature vector components $f+1,\ldots,CDIM$ with feature vector components $1,\ldots,f$ unchanged (i.e., $\mathbf{c}_{i^*}(t)=\mathbf{c}_{i^*}(t-1)$ for instrument I_B.

The generalization of the above instrument usage prioritization framework to more than two instruments and/or a set of targets follows directly from III and IV.

V. Conclusion

The prioritization frameworks for single and multiple targets introduced here may be useful for autonomously operating computer-based planning systems (e.g., onboard science craft such as satellite platforms, spacecraft, planetary orbiters, landers, rovers, etc.) to decide which previously detected and coarsely examined target or set of targets harbor the largest potential for an overall "knowledge gain" about an operational area if revisited or examined more closely. In addition the prioritization framework for instrument usage may provide guidance as to which instrument out of a suite of available instruments onboard a science platform has the largest potential to contribute to the above "knowledge gain" if used on these targets. Since instruments may differ in power consumption, time to take the measurement, and distance from the object to be examined, etc., a planning system can take into account these constraints together with the prioritization probabilities and may come up with an optimized "target-to-reexamine" and "instrument-to-use-for-reexamination" scenario, thereby paving the way to more autonomous reconnaissance missions.

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