A New Multiple Information Fusion Approach for Astronomical Navigation using Markov Random Field algorithm

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Abstract. Autonomous navigation is one of the key technologies to ensure the implementation of deep space exploration mission. Astronomical angle measurement information and stellar spectral velocity measurement information are usually used to estimate the real-time navigation state. According to the characteristics and requirements of deep space navigation, this paper proposes a novel method for information fusing using Markov Random Field approach, which integrates the navigation information including angle measurement, velocity measurement and combination of angle and velocity measurement, to realize continuous autonomous, real-time and high-precision navigation of deep space exploration. Considering the background of Mars exploration engineering mission, the observability and precision of the navigation method are analysed. The simulation results show that the method based on Markov Random Field can greatly improve the observability of the navigation system, effectively suppress the influence of measurement error, further improve the accuracy of navigation estimation, enhance the reliability of the navigation system, and provide a new technical approach to realize the high precision autonomous navigation of deep space exploration.

1. Introduction
Deep space exploration has the characteristics of long flight distance, multiple unknown factors of flight environment, complex flight procedures, large delay and loss of vehicle-ground communication, existence of tracking blind area and occlusion of celestial bodies, and high requirements for autonomy, which put forward higher requirements for navigation ability [1]. In order to ensure the implementation of deep space exploration engineering tasks in the future, improve the success rate of deep space missions, and reduce engineering and technical risks, autonomous navigation in deep space is one of the key technologies that must be and urgently need to be broken through.

Recent years, deep-space probes in many countries have been equipped with partial autonomous navigation function, and autonomous navigation has become an effective supplementary means of ground measurement and control. On the one hand, autonomous navigation of deep space exploration can overcome the limitations of ground radio navigation in real-time performance, operation cost and resources, and enhance the autonomous survival ability of deep space exploration; On the other hand, it can improve the accuracy and continuity of deep-space probe navigation and improve the reliability
of successful engineering. In some special flight stages, such as approach, flight around, landing, attachment and ascent rendezvous, the position and velocity information of the detector relative to the target object need to be acquired accurately. Autonomous navigation and control often have performance beyond ground measurement and control.

2. Multiple Navigation Information Fusion Using MRF
Astronomical autonomous navigation can be divided into angle measurement, distance measurement and velocity measurement according to the principle of observation [2]. Angular navigation takes the optical images of stars, planets and other celestial bodies as the observation quantity, combined with celestial ephemeris, detector attitude and other information to obtain the relative line of sight of the target celestial body, and further uses geometric relations or orbital dynamics to estimate the position and velocity of the detector [3]. The spectral characteristics and frequency shift involved in the astronomical optical information contain the velocity information of the detector. The instantaneous velocity can be estimated with high accuracy by making full use of the natural resources of space, such as obtaining the spectral velocity information directly. And the navigation information of velocity measurement is obtained [4]. The navigation information of angle measurement and velocity measurement is fused by using navigation filtering algorithm, and the integrated navigation information of angle measurement and velocity measurement is obtained [5]. This paper Markov Random Field is used to further fuse the above three navigation information, so as to effectively solve the problems of low instantaneous velocity estimation accuracy in angular navigation, divergence of position estimation accuracy of velocity measurement navigation with time, and unstable position estimation of combined angular and velocity measurement navigation.

2.1. Markov Random Field
Probabilistic analysis plays an important role in pattern recognition. All probabilistic inference and learning use the repeated application of sum rule and product rule. It is also advantageous to enlarge the analysis by graphical representation of the probability distribution, which is also called the probabilistic graphical model. In the perspective of graph theory, the probability graph model is a graph containing nodes and links. In the perspective of probability theory, probability graph model is a probability distribution, where each node represents one or a group of random variables, and the links of two nodes correspond to the relationship between two variables. MRF is a kind of undirected graphical model, in which the links in these models are not directional and it is also more suitable to express the soft constraints between random variables[6].

2.1.1. MRF Model. The MRF algorithm is applied to fuse the above three navigation information, so as to improve the accuracy of position estimation. In this paper, there are three methods for position estimation: A- angle measurement position estimation, B-velocity measurement position estimation, and C-angle and velocity combination position estimation. An undirected graph model is proposed for these three methods, as shown in the figure[7]:

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Figure 1. MRF model of fusion of three measurement methods for position estimation

It can be seen that MRF is composed of four nodes: purple represents the new estimated position obtained by combining the estimated positions of the previous three methods of MRF algorithm; green represents the estimated position of angle measurement method; blue represents the estimated position of velocity measurement method; black represents the estimated position of the combined method of angle measurement and velocity measurement. \( i \) represents the current observation node, and \( i-1 \) represents the previous node; \( s_1, s_2, s_3 \) and \( p \) are respectively the influence degree of the estimated position of corresponding method on the current observation node, which represents the correlation between the estimated position of other methods and the observation node, namely the weight factor. Distance can represent the position relation of two points in space. The distance information between the estimated position and the real detector position obtained by different methods determines the weight factor[8].

In particular, MRF model is defined by the following potential function:

1) The current node MRF estimate position and the previous MRF estimate position:

\[
\Psi = \rho \left( \lVert R_i - R_{i-1} \rVert \right)^2
\]

2) The current node MRF estimate position and the other three methods estimate position:

\[
\Phi = s_1 \left( \lVert R_i - A_i \rVert \right)^2 + s_2 \left( \lVert R_i - C_i \rVert \right)^2 + s_3 \left( \lVert R_i - (B_i - M) \rVert \right)^2
\]

The energy function of the model is:

\[
E(R, A, B, C) = \Psi + \Phi
\]

It defines the joint distribution given by \( R, A, B, \) and \( C. \)

\[
p(R, A, B, C) = \frac{1}{Z} \exp(-E(R, A, B, C))
\]

Where \( Z \) is a normalized constant:

\[
Z = \sum_{R,A,B,C} \exp(-E(R, A, B, C))
\]

In order to ensure the accuracy of the estimated position after fusion, the sample \( R \) with the maximum probability reset should be found. This requires that the energy function be minimized, where the initial variable is \( R_1 = A_1. \)

2.2. Simulation results

In this paper, MATLAB is adopted for data simulation processing. The data is 2000 steady-state data with a step length of 60 seconds. The navigation estimated position obtained by combining three original measurement methods through MRF algorithm is as follows:
Figure 2. Spatial distribution

As can be seen from the spatial distribution diagram in figure 2, the spatial distribution of the position estimated by MRF algorithm is much better than that based on velocity measurement, and the overall distribution is consistent with the real position.

Figure 3. The distance distribution diagram of the four methods estimated position and the real position

Figure 4. The distance distribution diagram of the three methods estimated position without velocity measurement position estimation and the real position
As can be seen from the figure 3 and figure 4, the estimated position distribution of MRF algorithm is stable, and the distance between most estimated positions and the real position is within 60. Only between the index of 1300-1500, the distance affected by the angle measurement method changes greatly, but its distance value is still smaller than the distance value of the angle measurement method, which indicates that the MRF algorithm is reliable in combining the navigation information estimated by angle measurement, velocity measurement, and angular velocity measurement.

3. Conclusion
In this paper, a probability distribution model defined by Markov Random Field is designed. The purpose of this model is to obtain a more accurate estimation position by integrating the estimation positions of three navigation information: angle measurement, velocity measurement, angle velocity and velocity measurement. The required energy function is generated according to the designed MRF model, and the new estimated position is calculated. By comparing the estimated positions obtained by the other three methods, it can be seen that MRF algorithm effectively fuses the estimated positions obtained by the above three methods, and gets an estimated position, which is closer to the real position. Moreover, the estimated position distribution based on this algorithm is stable. This algorithm can complete the fusion effectively and provide more suitable estimation position.

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References
[1] Li J.F., Cui W., Baoyin H.X. (2012) A Survey of Autonomous Navigation For Deep Space Exploration. J. Mechanics in Engineering. Commun., 34:1-9.
[2] Whittaker M.P, Linares R, Crassidis J.L. (2013) Photometry and angles data for spacecraft relative navigation.In: AIAA Guidance, Navigation, and Control Conference, Boston, MA, USA. pp. AIAA 2013-5196.
[3] Riedel J.E, Bhaskaran S, Desai S, et al. (1999) Autonomous optical navigation (AutoNav) Deep Space 1 Technology Validation Report. In:DESCANSO Symposium. Pasadena, CA, United States, pp. 2002:1-39.
[4] Zhang W, Chen X, You W, et al. (2013) New Autonomous Navigation Method Based on Redshift. J. Aerospace Shanghai. Commun., 30:32-33.
[5] Lightsey E.G., Mogensen A., Burkhart P.D., et al. (2008) Real-Time Navigation for Mars Missions Using the Mars Network J. Journal of Spacecraft and Rockets. Commun., 45:519-533.
[6] Kindermann R., (1980) Markov Random Fields and Their Applications. Contemporary Mathematics, Providence.
[7] Bishop C.M., (2006) Pattern Recognition and Machine Learning, Springer, America.
[8] Kittler J., Föglein J., (1984) Contextual Classification of Multispectral Pixel Data. J. Image and Vision Computing. Commun. 2: 13-29.