Optimal Scheduling for Geosynchronous Space Object Follow-up Observations Using a Genetic Algorithm

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ABSTRACT

Optical observations for space debris in the geosynchronous region have been performed for many years. During this time, observation strategies, processing techniques and cataloguing approaches were successfully developed. Nevertheless, the importance of protecting this orbit region from space debris requires continuous monitoring in order to support collision avoidance operations. So-called follow-up observations providing information for orbit improvement estimations are necessary to maintain high accuracy of the cataloged objects. Those serve a two-fold: For one, the orbits have to be accurate enough to be able to re-observe the object after a time of no observations, that is keeping it in the catalogue, secondly, the importance of protecting active space assets from space debris requires even higher accuracy of the catalogue orbits. Due to limited observation resources and because a space debris object in the geostationary orbit region may only be observed for a limited period of time per the observation night and telescope, efficient scheduling of follow-up observations is a key element. This paper presents an optimal scheduling algorithm for a robotic optical telescope network using a genetic algorithm that has been applied providing optimal solutions for catalogue maintenance. As optimization parameter the information content of the orbit has been used. It is shown that information content utilizing the orbit's covariance and the information gain in an expected update is a useful optimization measure. Finally, simulations with simulated data of space debris objects are used to study the effectivity of the scheduling algorithm.

1. INTRODUCTION

The space debris population around the Earth is permanently increasing. Objects in lower altitudes like in the Low Earth Orbit (LEO) are monitored by radar telescopes which are less dependent on weather and time conditions. Optical observations are used to observe space debris objects in higher altitudes. One of the most important and valuable orbit around the Earth is the Geosynchronous Earth Orbit (GEO). During the last years, several survey strategies have been developed to build up a catalogue of space debris objects for characterizing, collision avoidance and to improve the knowledge of the population size. For catalogue maintenance, additional observations are necessary to improve the orbit and to keep the orbit accuracy within a given limit. Since the GEO has to be observed with optical telescopes, the length of the observation night is the most limiting factor. This depends on the location site of the telescope and the season. Providing an optimum coverage of the GEO and to enable a continuous monitoring independent of seasonal limitations, a telescope network distributed around the earth both in the northern and southern hemisphere is required. A few telescope networks observing space debris in GEO are existing. The Space Surveillance Network (SSN) of the United States Strategic Command (USSTRATCOM) operates some optical sites around the world [6] and maintain two catalogues where only the restricted one is distributed globally. The International Scientific Optical Network (ISON) in Russia operates 35 observatories and has also global GEO coverage capability. But there is no catalog available. Finally, ESA is developing the technology and the architecture for a European network known as European Space Situational Awareness (ESSA) [2]. Next to these networks there is also the three telescope network of TAROT which is observing space debris in GEO [6]. Originally developed to observe Gamma-ray bursts it was expanded in 2009 by two additional telescopes and it started to monitor the GEO. However, there is no general catalogue of space debris objects distributed. Therefore, the German Space Operation Center (GSOC) builds up a small-aperture robotic telescope network in collaboration with the Astronomical Institute of the University of Bern. This telescope network will be used for surveillance observation to build up a space debris catalogue and for tracking observations for catalogue maintenance. More details are given in [3]. In this paper, an algorithm to schedule tracking observations will be shown. If once a determined orbit of a GEO object is good enough to re-observe this object after several days this orbit may be added to the catalogue. Simulations showed that after four observation sequences such a "secure" orbit may be determined [9] and an additional follow-up observation may be scheduled after up to one week. Depending on the used telescope and its Field of View (FoV), the position inaccuracy should be less than the half FoV to ensure a successful re-detection. Scheduling of follow-up observations requires knowledge of the target orbit and the available observatories. If the preferred observatory is selected, scheduler usually take into account the priority of an observation of an object [8] and time constraints. Latter ones have to be optimized corresponding to the reduction of the number of conflicts and to perform as many observations as possible. Since GEO objects could be visible over a longer time span of the observation night, the visibility constraints (e.g. phase angle, background illumination,...), which influence the detection probability, are not the only criteria to schedule an observation. The prediction of the effectivity of a future observation depending on the observation geometry and the orbit error covariance may be used to schedule an observation at the most effective time [4][5]. Scheduling of telescopes belongs to a class of NP-hard problems. Consequently, there are no known algorithms guaranteed to give an optimal solution and run in polynomial time. There are several techniques to handle such problems. In this work a genetic algorithm (GA) will be used to optimize the scheduling.

2. METHODS

2.1. Information Content

The advantages using a telescope network are the possibilities to perform more observations and to have more flexibility to schedule them as opposed to a single telescope. This allows to observe each object more often and to schedule observations at the most effective way. The effectiveness depends on the sensor-target geometry and therefore on the selected station and the observation time as well as on the uncertainty of the catalogued orbit.

The uncertainty of a catalogued orbit is given by the orbit error covariance matrix P. Furthermore, the observation geometry is given by the matrix H which consists of the partial derivatives of the observations with respect to the orbit state.

$$H = \frac{\partial h(x)}{\partial x} \tag{1}$$

$$= \begin{pmatrix} \dfrac{\partial h(az)}{\partial r_x(t)} & \dfrac{\partial h(az)}{\partial r_y(t)} & \dfrac{\partial h(az)}{\partial r_z(t)} & \dfrac{\partial h(az)}{\partial v_x(t)} & \dfrac{\partial h(az)}{\partial v_y(t)} & \dfrac{\partial h(az)}{\partial v_z(t)} \\ \\ \dfrac{\partial h(el)}{\partial r_x(t)} & \dfrac{\partial h(el)}{\partial r_y(t)} & \dfrac{\partial h(el)}{\partial r_z(t)} & \dfrac{\partial h(el)}{\partial v_x(t)} & \dfrac{\partial h(el)}{\partial v_y(t)} & \dfrac{\partial h(el)}{\partial v_z(t)} \end{pmatrix} \tag{2}$$

Using the equations of the Kalman filter for measurement update

$$K = P^- H^T (W^{-1} + HP^- H^T)^{-1} \tag{3}$$

$$P^+ = (I - KH)P^- \tag{4}$$

where K is the Kalman gain, P^- the propagated covariance matrix to the epoch of the observation, W the weighting matrix which is in this case the inverse of the observation error matrix and P^+ the updated orbit error covariance matrix a method is given which connects the three mentioned dependencies.

Usually all observations of the same object within a single FoV crossing constitute a so-called tracklet. A tracklet is a set of observations acquired over short period of time which presumably belong to the same object.

There are several different methods to calculate the information content of a new follow-up tracklet. In this study, the Shannon Information Content (SIC) introduced in [10] is used. Here, the information content is a measure of the reduction of entropy. We suppose S_{before} is the entropy of the knowledge $P(X)$ before and S_{after} is the entropy of the knowledge of $P(X, Y)$ with one additional follow-up tracklet. Then, the SIC is given by:

$$\begin{aligned} SIC &= S_{\text{before}} - S_{\text{after}} \\ &= S[P(X)] - S[P(X, Y)] \end{aligned} \tag{5}$$

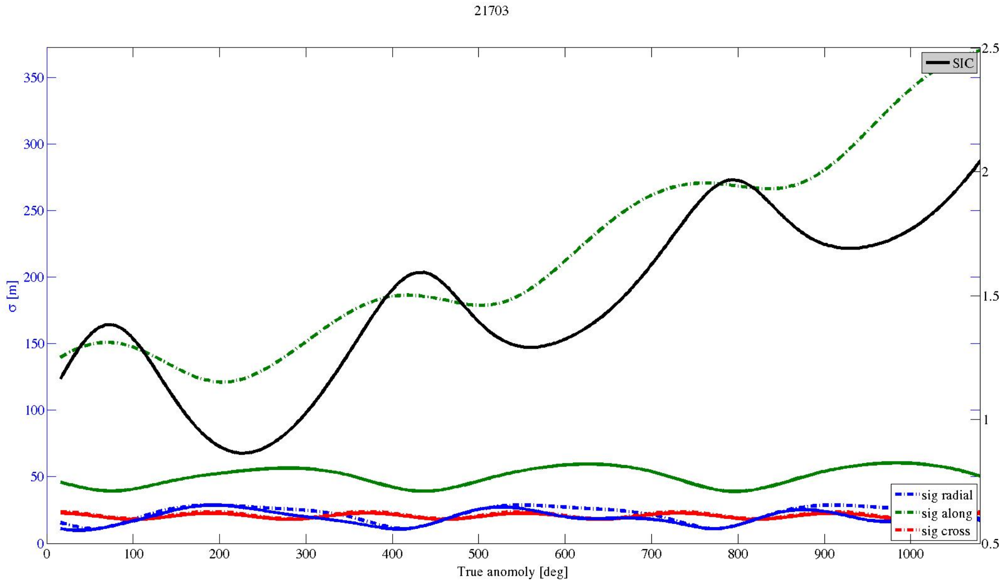


Fig. 1. Evolution of the position error (dashed lines) over three orbits for object 21703. The solid lines represent the improvement of the positon error by one new tracklet and the corresponding information content.

If we use the covariance matrix, then finally the SIC is given by:

$$SIC = \frac{1}{2}\ln|P^{-}_{\text{pos}}| - \frac{1}{2}\ln|P^{+}_{\text{pos}}| \tag{6}$$

$$= \frac{1}{2}\ln\left|P^{-}_{\text{pos}} \cdot (P^{+}_{\text{pos}})^{-1}\right| \tag{7}$$

where $|P^{-}_{pos}|$ denotes the determinate of the position covariance matrix before the observation and $|P^{+}_{pos}|$ the determinate of the positon covariance matrix after the observation.
In Fig. 1, an example of the influence on the position error of one additional tracklet during three orbits is shown. Here, a tracklet consists of nine coordinate pairs in azimuth and elevation within two minutes. The propagated position error in radial, along-track and cross-track are represented by dashed lines. If there is a new observation at a specific true anomaly these errors are reduced to a value on the solid line. The information content of each tracklet is represented by the black solid line and follows almost the along-track error line since this error is the major reason for the expansion of the position error ellipsoid. The disadvantage of this method is, that the information content has to be computed for every time when the target object could be observed. On the other side, this method ensures that for a given orbit with a corresponding covariance matrix the optimal available observation geometry depending on the observatory and observation time is selected.

2.2. Genetic Algorithm

Since scheduling belongs to NP class of problems, heuristics are used to solve this kind of problems. One of the most practical algorithms are the genetic algorithms (GA) inspired by the natural evolution. Their major advantages are the variability to treat any kind of problems and to approximate to solutions for even very complex optimization problems. The high efficiency of these algorithms is reached by the parallel search for solution during each iteration. But this involves also the risk to converge to a non-optimized solution since there is no procedure to develop such a GA. Therefore a lot of tests or simulations, respectivily, are required to ensure the capability of the developed algorithm.
Nevertheless, there is a guideline to develop a GA. At the beginning, a population of individuals have to be created. An individual in the sense of GA is a candidate solution to an optimization problem. Based on their fitness, individuals are selected and the two main operators are used to create better solutions. Sometimes it is an advantage to save the solution with the highest fitness value from the previous to the next generation to ensure that there is no worsening. Finally, there have to be criteria to terminate the algorithm. This may be e. g. the number of generations or the highest fitness value.

Fitness function The fitness function represents the optimization problem and their solution should be minimized or maximized, respectivily. A solution exists for each individual and the determined fitness value allows to compare the solutions. In this study, an indiviual represents a valid schedule for all telescopes. A valid schedule means, that an observation for each objects is only once scheduled and that this object is visible at the given time. Visibility constraints are maximum phase angle, minimum distance to the Moon and to the Earth's shadow, respectively. For the sake of simplicity, it is not possible to schedule an object if one of these conditions is violated. Each scheduled observation of an object j has an expected information content SIC_j at the given time according to Eq. (7). The fitness value F_i of each individual is the sum of all scheduled SIC_j values and is given by:

$$F_i = \sum_{j=1}^{N} SIC_j \tag{8}$$

Now, the optimization problem is given by:

$$\max F = \max \sum_{j=1}^{N} SIC_j \tag{9}$$

Initial population An initial population is created at the beginning of each GA. This happens usually randomly to secure a good coverage of the search area. In this study, the number of individuals and therefore the size of the population correspond on the number of chosen objects. Since some chosen objects have the same optimum observation time at the beginning or at the end of the observation night there is a need to ensure a high diversity of the initial population. Therefore the objects were prioritised by sorting according to their position error. Creating the first individual the first object (with the worst positon error) is chosen and the follow-up observation is scheduled at the optimum time during the night. All other observations where scheduled according to the priority of the object and as close as possible to the optimum time. After that the first object got the lowest priority. For the second individual, the observation of the new first object was scheduled at the optimum observations time and all other observations again according to the priority of the object. At the end, the object with the highest priority got the lowest one. This procedure was repeated until for each chosen object the observation was once scheduled at the optimum observation time. The remaining individuals were created randomly.

Selection Using Eq. (8), the fitness of each individual is calculated and according to that value individuals are selected for the two main operators in a GA. This allows selecting good solutions for further generations and to eliminate bad solution.
There are three common methods to select individuals: fitness proportionate selection, rank based selection and the competition selection. Simulations showed that for this application the rank based selection is the most promising method.
This method was developed to avoid a early convergence right in the beginning of the search. Instead of using the absolute fitness values of each individual all individuals are sorted according to their fitness values. Now, the rating of an individual depends on the position only. This leads that individuals with a high rank are selected with a higher probability in comparison with individuals with a lower rank. Furthermore, this causes also a longer search but increases the probability to find the global optimum. Even if there are many individuals with good fitness values the selection pressure is still high which avoids to get stuck in the search. Defining the selection probability, Baker [1] suggest following method: The individual with the highest rank get the expectation values $E_{\max}$ with $1 < E_{\max} < 2$. The expectation values of the worst individual is now given by $E_{\min} = 2 - E_{\max}$. Finally, the expectation values of any other individual is given by:

$$E(a_i) = E_{min} + (E_{max} - E_{min}) \frac{r(a_i) - 1}{n - 1} \tag{10}$$

where $r(a_i)$ is the rank of the individual a_i. The selection probability is then given by

$$p_s(a_i) = \frac{1}{n} E(a_i) \tag{11}$$

Baker suggested the value 1.1 for E_{max} and this value is also used in the described algorithm. Finally, the selection is performed using stochastic universal sampling with the selection probabilities $p_s(a_i)$.

Usually, the number of selected individuals matches the size of the population. Because of the selection probability, some individuals are selected several times and other ones not at all. This leads to the elimination of the worst individuals.
Ensuring that the fittest individual of the next generation is not worse than the fittest one in the current generation, elitism is used and the fittest individual is inserted directly to the next generation. But keep in mind that this individual still may be selected for both crossover and mutation operator, respectively.

Crossover The first operator is the crossover operator which allows big jumps in the search area. Here, two selected individuals are taken and at a given point an interchange occurs. At the end there are two new individuals with properties of the both parent individuals. There are approaches to interchange at a single point or at n-points what depends from the assignment. Finally in most cases a probability is defined when such a crossover may take place.
In the presented algorithm, a random point within a chosen individual is taken. Since each object has to be scheduled only once, an interchange of two objects between the selected individuals might produce a chain of interchanges until each object is scheduled once and both new individuals represent a valid schedule. Obviously, the visibility constraints need not be taken into account since the time when an observation of an object is scheduled does not change. Instead of defining a probability to allow such a crossover, the new individuals are only accepted when their fitness value is better than the average of the whole current population. Otherwise, the parent individuals get to the next generation. In the end, the size of the population of the next generation is equal to the size of the previous population.

Mutation The second operator used in GA is the mutation which is used to make small jumps in the search area. It is still in discussion which one is more useful but in the end a good balance between crossover and muations should be guaranteed [7].
In this scheduling algorithm, a random number of individuals is selected for mutation. For each selected individual, a random number of mutations may take place. At each mutation, a selected observation is interchanged with the observation scheduled before or after the selected one. If this interchange is possible taking into account the visibility constraints of the object, the sum of $SIC_j + SIC_{j+1}$ is compared to the previous situation. This mutation is accepted if there is an improvement of the fitness.

3. RESULTS

Simulations were used to demonstrate the effectivity to schedule observations according to their information content and the functionality of the GA. Performing these simulations a catalogue of space debris objects was created.

3.1. Catalogue

Base for the simulated space debris object catalogue is the USSTRATCOM catalog from 2015-01-01. Using the ranges of the orbital elements given in Tab. 1, 1187 objects were selected. The simulated observation campaign lasted from 2015-01-01 to 2015-03-31. During this time 720 objects were visible from the Zimmerwald observatory, Switzerland. For each of these objects, a random number of observation nights within the campaign was chosen whereas a minimum of 20 observation nights was required. On every observation night two tracklets, each consisting of 10 observations with an arc lenght of two minutes, were simulated. All observations have a standard deviation of $1''$. For simplification, an equal area of $10.0\,\mathrm{m}^2$ and a weight of $200\,\mathrm{kg}$ was chosen.

Tab. 1. Orbital elements

35 000 km	$\leq$	a	$<$	50 000 km
0.0	$\leq$	e	$<$	0.3
0.0°	$\leq$	i	$<$	20.0°
0.0°	$\leq$	Ω	$<$	360.0°
0.0°	$\leq$	ω	$<$	360.0°
0.0°	$\leq$	M	$<$	360.0°

3.2. Performance of the Shannon Information Content

Keeping objects in the catalogue requires follow-up observations. Usually, such observations are scheduled when the position error exceeds a given limit. Performing the following simulations, a maximum along-track error of 1400 m was allowed. If this value was exceeded, a new observation during the following night was required.
In Fig. 2(a), the progress of the information content is shown. The red dots represent when the object is not visible whereas the green dots represent the possible observation time. Finally the black cross shows the time when the highest information content of a new observation is expected. Since the along-track error is the main factor for the expanding error ellipsoid, Fig. 2(b) shows its evolution of this error during the observation night.
Illustrating the effect of a new observation tracklet on the position error, one object from the catalogue was used. Starting at epoch MJD = 57120.5, tracklets with a stepsize of 600 s were simulated during 24 h. Afterwards the catalogued orbit and one tracklet were used to determine an improved orbit. Figure 3(a) shows the along-track error of these 145 improved orbits at epoch MJD = 57121.5. The green dots represent the tracklets at the visibility time whereas the red dots represent tracklet which were not able to schedule. The black cross represents the orbit where the tracklet was scheduled at the optimal time according to the information content.
Finally, all determined orbits were propagated over one week and the results are shown in Fig. 3(b). The black cross, which represents the orbit with the optimized scheduled follow-up tracklet, is nearly at the minimum. The gap to the minimum may be explained by the fact that the whole position error was minimized.

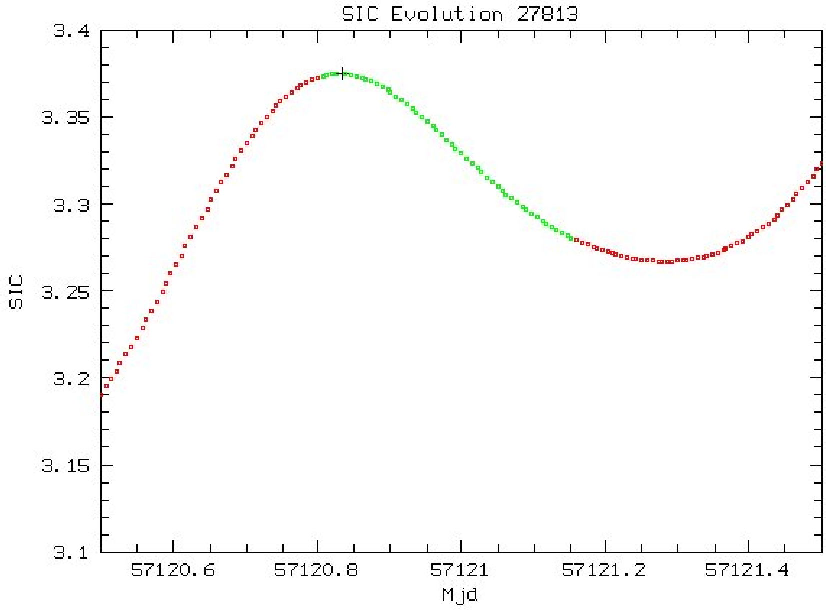
3.3. Performance of the Genetic Algorithm

Using the population mentioned above, simulations were performed to illustrate the performance of the GA regarding to the quickness, convergence and quality. In the used version of the scheduling algorithm, the visibility of each object was limited by a minimum elevation of 20° above the local horizon. Furthermore, a maximum phase angle of 100° and a minimum distance of 20° to the Moon and galactic plane, respectivily, were assumed to allow the scheduling of an object.
Three telescope were considered (see Tab. 2) where only Zimmerwald (Switzerland) and Sutherland (South Africa) will belong to the future SMARTnet. OGS (Tenerife) was selected to have one in longitude displaced observatory. Depending on the season observations were scheduled more in Sutherland (summer) or more at OGS (winter). Only a few observations were scheduled at Zimmerwald because of the visibility constraints.

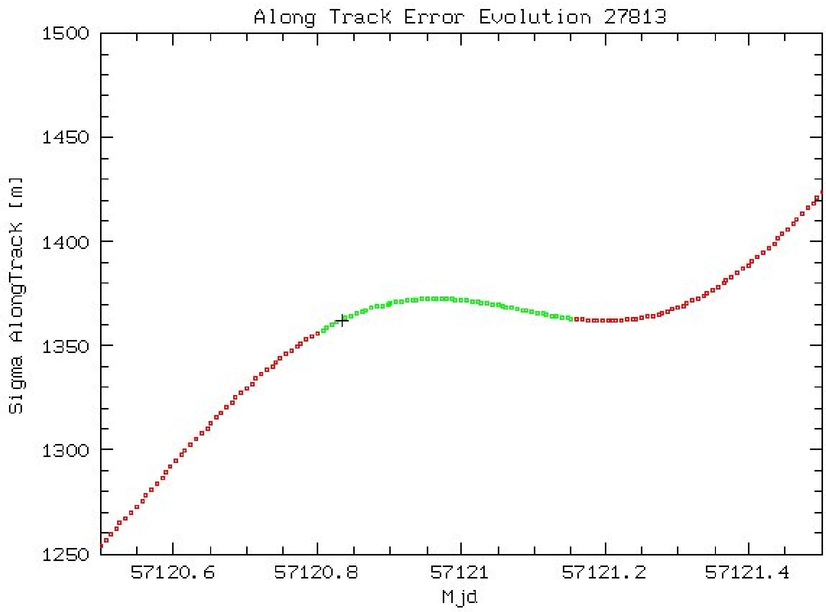
Tab. 2. Telescope location:
Longitude λ, Latitude φ and Height h

	$\lambda[°]$	$\varphi[°]$	h[m]
Zimmerwald	7.465	46.877	970
Sutherland	20.813	-32.937	1700
OGS	-16.304	28.167	2400

During the presented observation night 2015-04-08 a total observation time of about 1700 min was available and 436 objects from the catalogue were visible. Depending on the evolution of the covariance matrix and therefore of the position error, 62 objects were selected if the threshold value was exceeded. At the beginning of the scheduling process, each object was allocated to one telescope according to the highest information content of a new observation. After that each schedule for a specific telescope was optimized according to Eq. (9) using the GA. If the information content of a scheduled observations at the given telescope was less in comparison with the highest one at another possible telescope or observations for one object could not be scheduled at all, another telescope was assigned.
Fig. 4 shows the highest fitness value in each generation. Each colour represent one run of the GA with randomly chosen positions for crossover and mutation. Finally, after about 600 generations the algorithm converted to the optimum and therefore the optimized schedule for all telescopes was created.

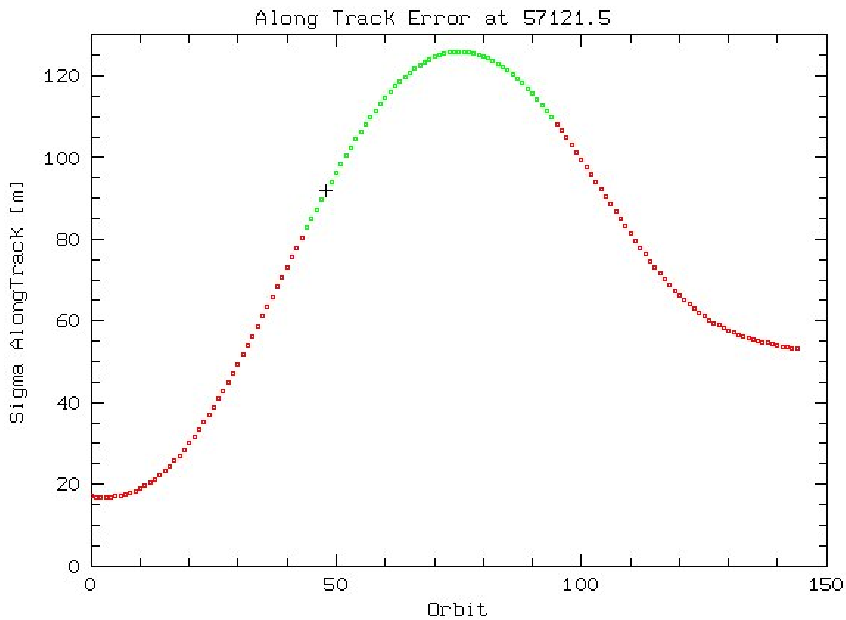


(a) Information content

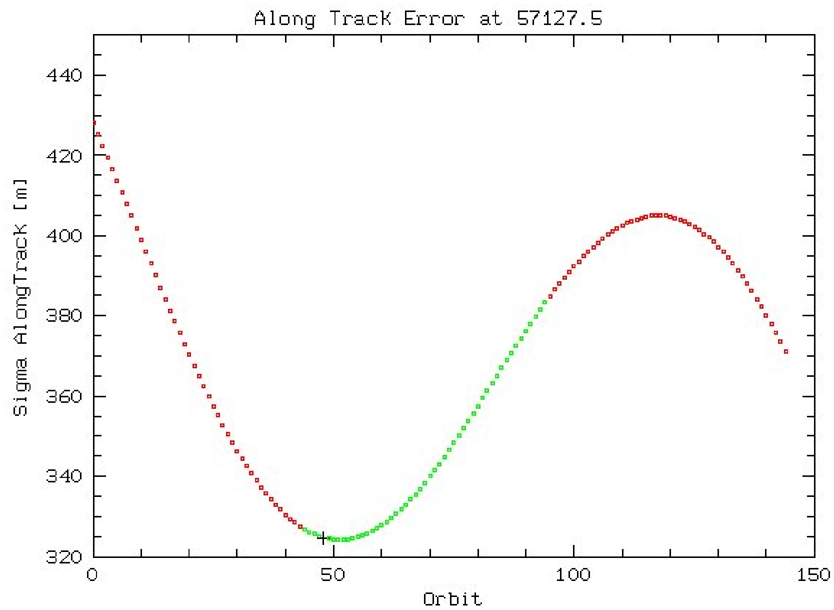


(b) Along-track error

Fig. 2. Evolution of the information content and the along-track error of catalogue object 27813 during the observation night 2015-04-08. The green dots represent the time of visibility, the red dots represent the time of non-visibility. The black cross remarks the optimum observation time.



(a) at MJD=57121.5



(b) at MJD=57127.5

Fig. 3. Along-track error of object 27813 at different epochs for 145 determined orbits using one additional follow-up tracklet for orbit improvement. With a stepsize of 600 s one follow-up tracklet was simulated and an orbit determined. The green dots represent the time of visibility, the red dots represent the time of non-visibility. The black cross remarks the determined orbit with the optimum scheduled tracklet.

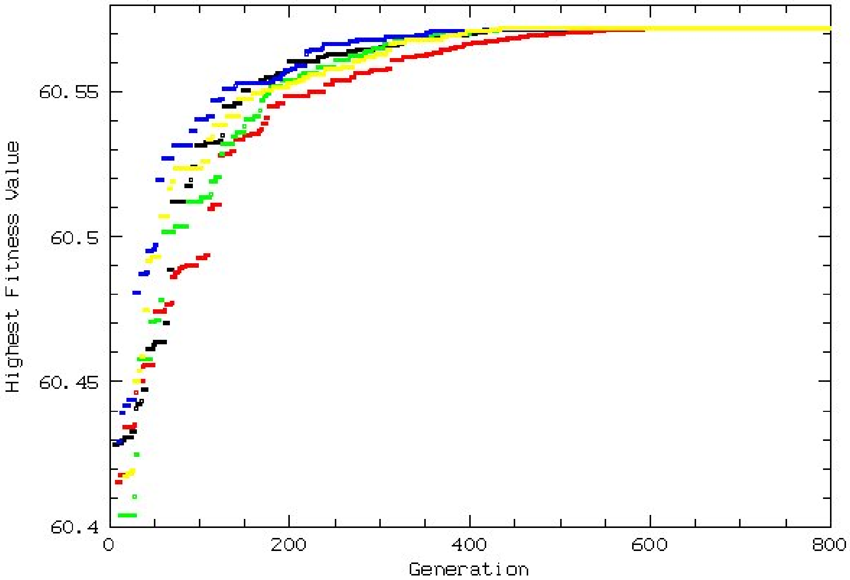


Fig. 4. Convergence of the GA finding the optimum solution scheduling observations for 62 objects. Each colour represents a run of the GA using random positions for crossover and muation operator, respectively.

4. CONCLUSIONS

In this work an optimized scheduling algorithm was introduced. The information content of a follow-up tracklet was based on the influence to reduce the positon error covariance. This reduction depends on the used observatory, the time of the observation and the already determined covariance of the object. Scheduling observations corresponding to this information content leads to a better result in comparison with scheduling the other methods according to simple schemes which try to ensure that the position error may be kept under a treshhold over a longer time. Furthermore, it allows to minimize the number of necessary follow-up observations for catalogue maintenance.
The algorithm should schedule the observations for each selected object in the optimum way. This requires to schedule as many observations as possible and to maximize the information content of each observation. Scheduling belongs to the class of NP-hard problems and therefore heuristics offer techniques to solve this kind of problems. Because of the effectivity of genetic algorithms, such an algorithm was developed and introduced. Several telescopes and visibility constraints were taken into account to perform simulation that ensure a realistic scenario scheduling follow-up observations for catalogue maintenance. Nevertheless some ideal assumptions were used to introduce this algorithm. All catalogued objects had the same size and weight and there was no function taking into account a detection probability.
The results show that all required observations of the selected objects are scheduled and that the genetic algorithm converges to the optimium. Using random positions for crossover and mutation operators, the algorithm converges after about 600 generation to the maximum.

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