Design and simulation in SAR satellites' task planning system using genetic algorithm with entropy operator

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Abstract

Purpose – This paper aims to innovatively propose to improve the efficiency of satellite observation and avoid the waste of satellite resources, a genetic algorithm with entropy operator (GAE) of synthetic aperture radar (SAR) satellites' task planning algorithm.

Design/methodology/approach – The GAE abbreviated as GAE introduces the entropy value of each orbit task into the fitness calculation of the genetic algorithm, which makes the orbit with higher entropy value more likely to be selected and participate in the remaining process of the genetic algorithm.

Findings – The simulation result shows that in a condition of the same calculate ability, 85% of the orbital revisit time is unchanged or decreased and 30% is significantly reduced by using the GAE compared with traditional task planning genetic algorithm, which indicates that the GAE can improve the efficiency of satellites' task planning.

Originality/value – The GAE is an optimization of the traditional genetic algorithm. It combines entropy in thermodynamics with task planning problems. The algorithm considers the whole lifecycle of task planning and gets the desired results. It can greatly improve the efficiency of task planning in observation satellites and shorten the entire task execution time. Then, using the GAE to complete SAR satellites' task planning is of great significance in reducing satellite operating costs and emergency rescue, which brings certain economic and social benefits.

Keywords Aerospace engineering, Satellite observation, Task planning problem, Improved genetic algorithm

Paper type Research paper

Nomenclature

Symbols

ΔS	= increase of entropy ($J \cdot mol^{-1} \cdot K^{-1}$);
ΔQ	= heat absorbed ($J \cdot mol^{-1}$);
T	= temperature (K);
P	= pressure (Pa);
V	= volume (m^3);
n	= number of molecules (mol);
R	= gas molar constant ($J \cdot mol^{-1} \cdot K^{-1}$);
$avggap$	= average task gap (–);
$count$	= number of single-orbit tasks (–);
gap_i	= the i-th task gap (–);
$startseq_i$	= start time of the i-th sequence (–);
$endseq_i$	= end time of the i-th sequence (–);
s^2	= variance (–);
s	= standard deviation (–); and
$entrophy$	= value of entropy (–).

Definitions, acronyms, abbreviations

SAR	= synthetic aperture radar;
GAE	= genetic algorithm with entropy operator;
GA	= genetic algorithm;
CX	= cycle crossover; and
TLE	= two-line orbit element.

Introduction

The task planning system is an important component of satellite observation task management and control platforms of ground service. It mainly solves the problem of resource contentions and conflicts in task management of satellite observation and optimizes the efficiency of satellite usage. There are many researchers focusing on task planning, who have built different models and have applied different intelligent algorithms to find the solution of their models. In

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Aircraft Engineering and Aerospace Technology
93/7 (2021) 1236–1242

[ISSN 1748-8842]
[DOI 10.1108/AEAT-11-2020-0247]

Received 24 November 2020
Revised 23 April 2021
21 May 2021
9 June 2021
Accepted 5 July 2021

comparison with these algorithms, the statistical analysis and the simulation result will verify the feasibility and advantages of the genetic algorithm with entropy operator (GAE).

Task planning problem

Task planning is a kind of optimization problem with multiple constraints, where heuristic algorithms are usually used to find the optimal solution such as greedy algorithm, genetic algorithm and ant colony algorithm (Huicheng *et al.*, 2013; Pei *et al.*, 2011; Mok *et al.*, 2019). The characteristic of the task planning problem is that it is very complex due to quantities of constraints so that it is difficult to find the absolute optimal solution. Some researchers focused on the constraints and raised the Tabu Search Heuristic Algorithm to find the most optimal schedule for the given orbit (Cordeau and Laporte, 2005). There were also some researchers who adopted a kind of heuristic algorithm to work out their lifecycle model of satellite observation task from the aspect of system engineering, in which they took the whole process of the task into consideration to shorten the execution time so that it could meet the time requirement of emergency conditions (Gang *et al.*, 2013).

Genetic algorithm

Genetic algorithm (GA) is an effective intelligent algorithm for solving task planning problems. It has the characteristics of simple operation and the ability to find the global optimal solution. Therefore, it has a wide range of applications in optimization problems. At present, there are many intelligent algorithms applied in satellite task planning, which basically meet the requirements. However, how to improve existing algorithms and reduce the number of satellite revisits has become a vital research focus, which is conducive to reducing operating costs and improving response speed.

The researcher, Baek, applied a new GA to simulate the actual satellite task planning problem and designed a graphical user interface for autonomous satellite task operation to raise the whole efficiency and convenience (Baek *et al.*, 2011). Other researchers proposed the concept of time margin to reflect the satisfaction degree of task urgency requirements based on the features of emergency observation. They also constructed a priority-time-based planning target and confirmed a series of constraints to find the solution of the model by using GA (Chao *et al.*, 2016).

At the current stage, the longest observation time of a single orbit is always regarded as the most important factor in judging the algorithm efficiency in task planning problems. The planning results may cause the uneven distribution of orbit tasks, the insufficient utilization of satellite resources, the increase of revisit time and the low efficiency of single orbit observation. Through applying entropy operator in GA, tasks in a single orbit can be arranged evenly and the satellite resources can be used as much as possible. The GAE provided by this article gives more comprehensive consideration to the whole cycle of a single orbit and allocates the task sequence more reasonably to reduce the number of satellite revisits.

Entropy and application

Entropy in thermodynamics

Entropy is a function that describes the status of a system. The reference value and variation of entropy are usually adopted in analysis and comparison. It is widely used in cybernetics, probability theory, number theory, astrophysics, life sciences and many other subjects. In different fields, entropy has different definitions and different combination methods.

As a variable to describe the disorder of a system, the concept of entropy was first raised by Clausius in 1865. Clausius defined the increase and decrease of entropy ΔS in a thermodynamic system: in a reversible process, the total amount of heat ΔQ used at a constant temperature T can be expressed as equation (1):

$$\Delta S = \frac{\Delta Q}{T} \tag{1}$$

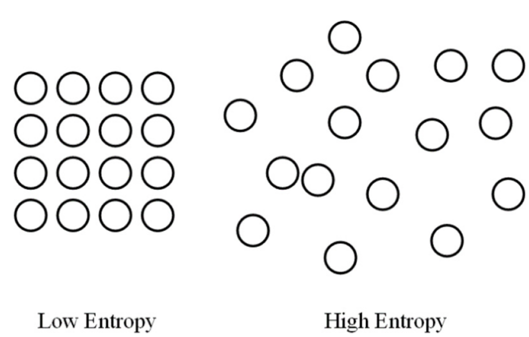
At the same temperature, the object transfers from liquid to gas; the heat of the system increases and the entropy value increases accordingly. Therefore, the entropy value is a physical quantity that reflects the disorder of the object. In the solid, liquid and gas, the entropy value in gas systems is highest and the entropy value in solid systems is lowest.

$$PV = nRT \tag{2}$$

According to the Ideal Gas Law shown in equation (2), it can be known that for a certain amount n of gas molecules at a certain temperature T, the gas volume V and pressure P are inversely proportional and the entropy of the gas system can be increased by increasing the energy of the gas system. When the pressure is under one standard atmosphere, if the gas has more energy, the volume will expand more. From the microscopic perspective, the volume is determined by the distance between gas molecules. When the pressure is constant, the farther distance between the molecules means the larger gas volume and vice versa.

In chemistry and thermodynamics, the entropy value reflects the degree of chaos in the system as shown in Figure 1. Higher entropy means farther molecular distance and the system becomes more chaotic. On the contrary, lower entropy means closer molecular distance and the system becomes more stable.

Figure 1 System entropy concept



Application of entropy

The concept of entropy in thermodynamics has been extended and transformed to the principle of the entropy increase, the maximum entropy principle, the minimum entropy production theorem, the information entropy and other concepts, which have a huge influence on probability theory and mathematical statistics.

The main idea of the maximum entropy principle is that when only part of the knowledge about unknown distributions is available, the probability distribution that meets these but has the largest entropy value should be selected (Jaynes, 1957). Phillips and his team introduced the use of the maximum entropy method for modeling species geographic distributions with existing data (Phillips *et al.*, 2006). Holder used the maximum entropy model and landscape characteristics to predict the geographic distribution of pelagic fishes (Holder *et al.*, 2020). When some values under certain limited conditions are known, there are many types of pelagic fish distributions and the distribution with the largest entropy is selected as the prediction result, which is an effective treatment method and criterion.

The minimum entropy production is based on the entropy increase theorem and can find the optimal and stable form of the system (Rusheng, 1985; Fasheng, 1995). Jing used the definition of individual density to measure the population diversity of the genetic algorithm and used the elitist strategy to drive the rapid decline of population entropy (Jing *et al.*, 2019). When the population diversity is too low, the selection strategy based on the minimum entropy generation is used to generate a new population to ensure population diversity.

Design of genetic algorithm with entropy operator

Although GA has a great performance in task planning, it still has problems in uneven distribution of single-orbit tasks and the lack of efficiency in the late period of the algorithm. Figure 2 shows the results of GAE in different task planning for the same orbit. When the entropy value of the single-orbit planning result is low, the gap between tasks is small, which causes the tasks to be concentrated in a certain segment of the entire orbit and wastes other parts of the orbital resources. It also makes the satellite need to surround several circles to complete other tasks. When the entropy of the single-orbit planning result is high, the tasks are evenly distributed in the entire orbit and the overall consideration is taken into account during planning. It means while ensuring the duration of the single-orbit observation at the same time, the overall efficiency of satellite observation is improved.

Design of task planning genetic algorithm

Imitating the natural law of survival of the fittest in GA, the studied problem is coded by the GA and then the optimal individual is iterated through a certain fitness function for human manipulation and selection.

- *Encoding*

As an individual, each chromosome contains a complete set of task sequencing and several genes. Each gene represents a task in each plan which includes the start time, the end time, the wave position and some other information.

Figure 3 shows an example of a chromosome with 12 tasks in one orbit. The reasonable arrangement of tasks in a track will be gotten by the GA. Under many constraints, different sequences will lead to different satellite revisit times. With the help of GA, the chromosome with the highest fitness can be found and converted into mission planning results through decoding.

- *Selection*

The GA calculates the fitness of each chromosome to determine whether the chromosome has a higher probability of being selected or not. The fitness function usually includes factors such as the observation time of a single orbit and the duration of key areas. The algorithm gives different weights to different indicators and artificially adjusts the expected

Figure 2 Different entropy in task planning result

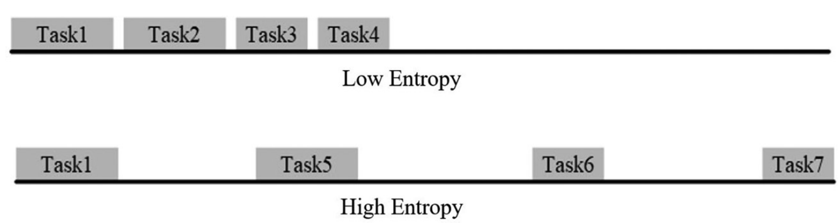


Figure 3 Diagram of one chromosome planning result

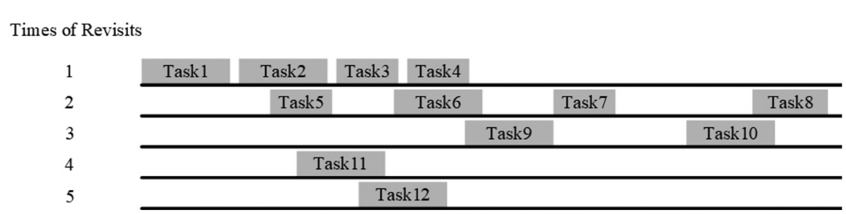
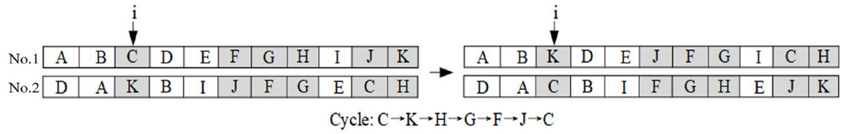


Figure 4 Chromosomal cycle crossover



direction of population evolution and finally selects the most optimal individual through iteration.

- *Crossover*

The process of parent generation to offspring is called chromosome crossover. In the sorting algorithm, the crossover of chromosomes is to randomly select two segments of the two chromosomes for crossover. If a sorting conflict is encountered, the sorting of the new chromosome will be adjusted to complete the crossover. One of the crossover methods is cycle crossover (CX). It selects the No.1 gene on a parent randomly, finds the gene number at the corresponding position of the other parent, goes back to the position where the first parent finds the gene with the same number and repeats the previous work until a circle is formed. The position of all genes in the ring is the last selected position. Then use the gene selected in the parent chromosome No.1 to generate offspring, make sure the position corresponds and finally put the remaining genes in the parent chromosome No.2 into the offspring. The other offspring are obtained in the same way. An important characteristic of CX is that multiple crossing positions can be obtained by selecting one position randomly (Figure 4).

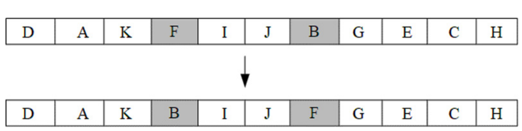
- *Mutation*

There is a certain probability of chromosomal mutation in chromosomes. Change the sequence of a certain gene or several genes in the chromosome and readjust the sequence of the chromosome to complete the mutation. The chromosome mutation model is shown in Figure 5.

Entropy operator

The entropy operator is introduced into the fitness function of the traditional genetic algorithm. The entropy operator reflects the disorder of the sort. If the entropy value of the sort is higher, the task distribution will be more uniform.

Figure 5 Chromosomal mutation



Then, the low entropy value indicates that the task distribution is concentrated.

The entropy operator is represented by calculating the standard deviation of the single-orbit task gap. When a single orbit has only one task, the entropy value is zero. When there is more than one task in a single orbit, the entropy calculation is performed. Assuming that the total duration of a single orbit is 5,700 s, the average task gap is shown in equation (3):

$$avggap = \frac{5700}{count - 1} \tag{3}$$

in which, *avggap* is the average task gap and *count* is the number of single-orbit tasks.

In a task sequence, the time between tasks is the task gap, which can be expressed as equation (4).

$$gap_i = startseq_i - endseq_{i-1} \tag{4}$$

The variance s^2 of a task ranking can be expressed as equation (5):

$$s^2 = \sum_{(i-1)}^{(count-1)} \frac{(gap_i - avggap)^2}{count - 1} \tag{5}$$

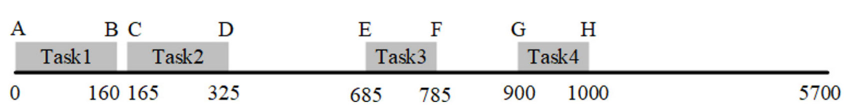
And convert the variance to the standard deviation s shown in equation (6):

$$s = \sqrt{\frac{\sum_{i=1}^{(count-1)} (gap_i - avggap)^2}{count - 1}} \tag{6}$$

Because a larger standard deviation means a more concentrated task and a large entropy means a more dispersed task. At the same time, considering that the magnitude of the entropy value needs to be equivalent to the observation time of the tasks and the duration of the key area, the conversion relationship between the standard deviation and the entropy value is constructed by equation (7):

$$entropy = \frac{10000}{s} \tag{7}$$

Figure 6 Example for entropy calculation



Adding the entropy operator into the fitness calculation of the GA and replanning the same orbit can allow individuals with higher entropy in the offspring to be more likely to be selected, thereby improving satellite efficiency and reducing satellite revisits time.

Example for entropy operator

Figure 6 shows the task planning result of a certain orbit revisit.

A total of 4 tasks are planned for this revisit and the entropy value of this revisit is calculated according to the entropy calculation equations (3–7):

$$avggap = \frac{5700}{3} = 1900$$

$$gap_1 = 5, \quad gap_2 = 300, \quad gap_3 = 115$$

$$s^2 = \frac{\sum_{i=1}^{3} (gap_i - 300)^2}{3} = 3.11 \times 10^6$$

$$s = \sqrt{\frac{\sum_{i=1}^{3} (gap_i - 1900)^2}{3}} = 1764$$

$$entropy = \frac{10000}{s} = 5.67$$

The calculation shows that the entropy of the planning result of this revisit is about 5.67, which is relatively small. If there is a better result, the probability of this chromosome being selected in the genetic algorithm will not be very large.

Algorithm simulation and result analysis

The Earth observation data based on the two-line orbital element (TLE) sets are taken to validate the algorithm. The TLE database includes the satellite number, orbital inclination, eccentricity, number of circles around the earth in a day and other information of various application satellites such as meteorological satellites and earth resource satellites. The original satellite orbital data (Kelso, 2020) is downloaded from the Celestrak website to simulate and calculate the revisit time. Then, some constraints are set before the observation experiment: the duration of a single observation is 160 s; the constraint of multiple imaging for a single orbit is 4 times and the time interval between turning on and off is 110 s.

Among the 288 satellite orbital data, there are 41 orbits to plan. The data of 41 orbits are simulated by both traditional GA and GAE. In GA, the weight of total observation time is 0.3 and the weight of key area observation time is 0.7. In GAE, the weight of total observation time is 0.2; the weight of key area observation time is 0.6 and the weight of entropy value is 0.2. The results of 41 orbital revisit times and the variations between GA and GAE are shown in Table 1.

From the results of 41 planned orbital data in Figure 7, the revisit time of 13 orbits is reduced by 1–4 times; the revisit time of 22 orbits remains unchanged and the revisit time of 6 orbits is increased by one. Through implementing the entropy operator in GA, 85% of the data in Table 1 are unchanged or decreased. In total, 30% of the data have been significantly optimized and the revisit time of optimized orbit is more than 10 times, which indicates that the GAE can perform better than the traditional genetic algorithm in the problem of orbital optimization with multitasks.

Table 2 gives the observation time of each revisit in four detailed different orbits. The cumulative observation time of each revisit in the four orbits shown in Figure 8 is calculated from the sum of data in Table 2, from which the number of

Table 1 Comparison of experimental result of GA and GAE

Orbit no.	Revisit time of GA	Revisit time of GAE	Variation
1	17	16	−1
2	20	17	−3
3	8	8	0
4	8	8	0
5	22	22	0
6	21	21	0
10	35	34	−1
13	15	14	−1
14	18	18	0
16	23	22	−1
18	7	7	0
19	9	9	0
20	15	15	0
24	18	18	0
29	16	17	+1
30	16	17	+1
35	15	15	0
37	23	23	0
43	16	16	0
47	16	16	0
64	7	8	+1
65	7	7	0
66	32	32	0
68	23	24	+1
71	33	30	−3
75	24	20	−4
77	14	12	−2
89	12	11	−1
91	18	18	0
97	27	27	0
107	26	27	+1
113	30	27	−3
133	21	20	−1
139	11	10	−1
146	29	28	−1
158	22	22	0
174	23	23	0
178	19	20	+1
205	32	32	0
210	15	15	0
216	9	9	0

Figure 7 Variation of revisit time of GAE

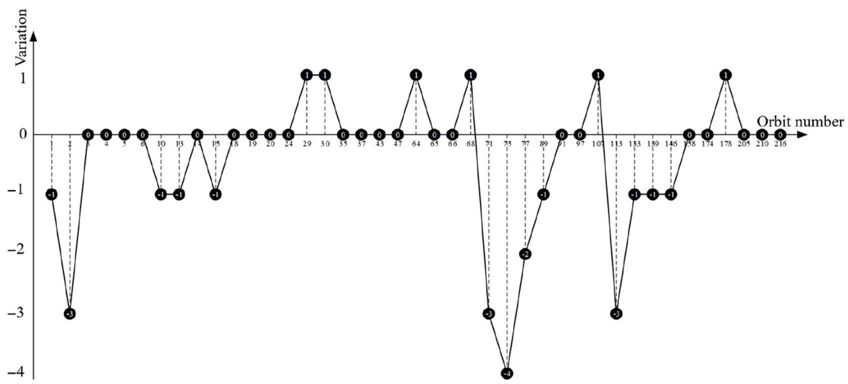
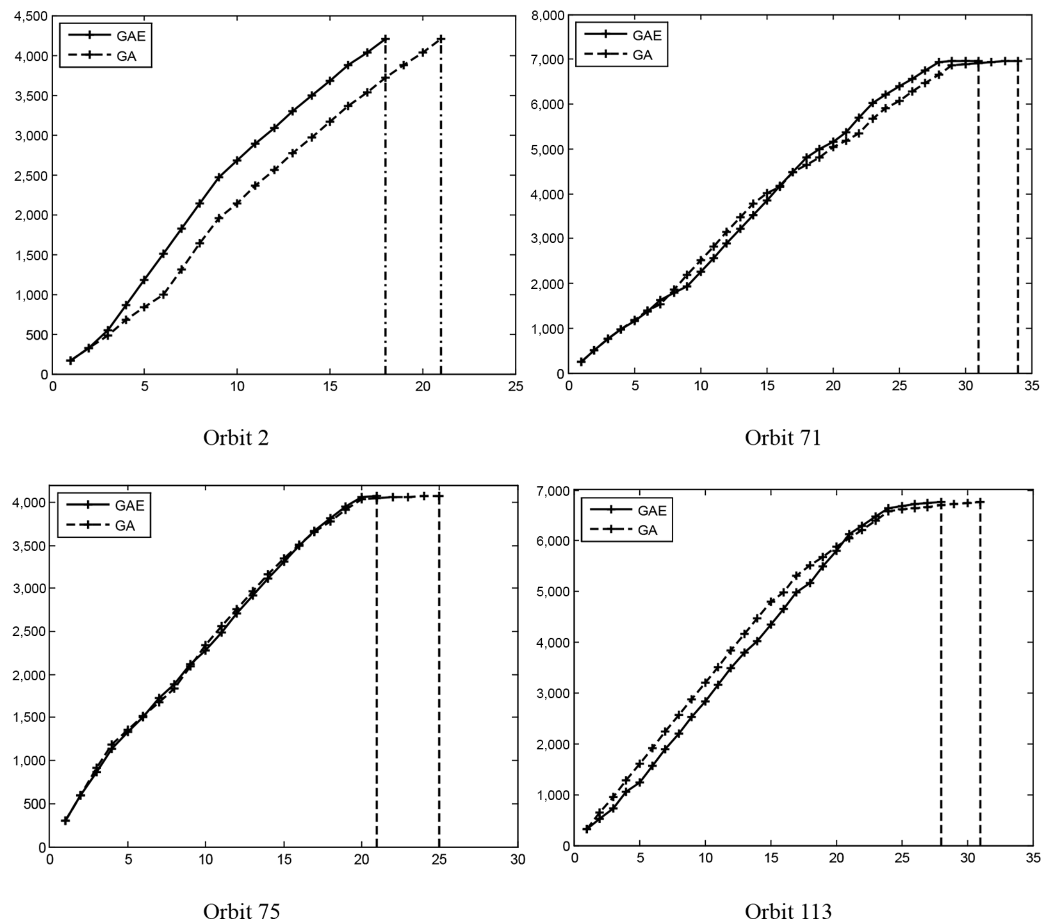


Figure 8 The cumulative observation time of each revisit in four different orbits



revisits is significantly reduced. Therefore, the efficiency of GAE is much higher than that of GA.

Conclusion

Due to the introduction of the entropy operator, the GAE has obvious advantages over traditional algorithms when dealing with multiple tasks and has equivalent efficiency with traditional genetic algorithms when dealing with common volume orbit data.

In general, the GAE can effectively solve the problems of low efficiency in the later period of other similar algorithms and the uneven distribution of satellite resources in traditional genetic algorithms. It can consider the overall expectation of the task planning, further reducing the satellite revisit time and improving the satellite work efficiency to a great extent.

Table 2 Observation time of each revisit in four different orbits

Orbit no.		2		71		75		113	
Algorithm		GA	GAE	GA	GAE	GA	GAE	GA	GAE
Observation time of each revisit	0	160	160	244	244	297	297	320	320
	1	160	160	267	248	296	298	320	203
	2	160	223	250	270	316	276	320	203
	3	193	320	206	204	278	270	320	320
	4	160	320	214	201	169	193	320	198
	5	160	320	208	209	160	169	320	320
	6	320	320	154	244	160	227	320	320
	7	320	320	320	158	160	160	320	320
	8	320	320	320	153	254	225	320	320
	9	191	213	320	320	250	160	320	320
	10	212	209	320	320	225	213	320	320
	11	207	205	320	320	195	223	320	320
	12	204	200	320	320	205	202	320	320
	13	204	198	320	320	197	198	320	217
	14	197	194	221	318	189	196	320	320
	15	191	190	157	320	154	190	190	320
	16	177	167	320	320	146	172	320	320
	17	176	160	156	320	131	145	199	188
	18	167	/	160	186	129	129	169	320
	19	160	/	236	156	127	119	202	320
	20	160	/	158	226	12	7	177	320
	21	/	/	156	320	7	/	160	167
	22	/	/	320	320	6	/	176	176
	23	/	/	242	200	5	/	179	176
	24	/	/	155	187	7	/	42	38
	25	/	/	221	156	/	/	33	30
	26	/	/	182	195	/	/	23	20
	27	/	/	195	177	/	/	23	19
	28	/	/	200	16	/	/	23	/
	29	/	/	32	7	/	/	20	/
	30	/	/	27	7	/	/	19	/
	31	/	/	21	/	/	/	/	/
	32	/	/	11	/	/	/	/	/
	33	/	/	7	/	/	/	/	/
	Total	4,199	4,199	6,960	6,962	4,075	4,069	6,755	6,755

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