The Problem of Fingerprints Selection for Topological Localization

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Abstract—**Visual navigation is extensively used in contemporary robotics. In particular, we can mention different systems of visual landmarks. In this paper, we consider one-dimensional color panoramas. Panoramas can be used for creating fingerprints. Fingerprints give us unique identifiers for visually distinct locations by recovering statistically significant features. Also, it can be used as visual landmarks for mobile robot navigation. In this paper, we consider a method for automatic generation of fingerprints. Since a fingerprint is a circular string, different string-matching algorithms can be used for selection of fingerprints. In particular, we consider the problem of finding the consensus of circular strings under the Hamming distance metric. We propose an approach to solve the problem. In particular, we consider the center string problem, the center circular string problem, and the center circular string with fixed letters problem. We obtain an explicit reduction from the center circular string problem to the satisfiability problem. We propose a genetic algorithm for solution of the center circular string problem. Also, we propose a genetic algorithm for the prediction the effectiveness of the use of special algorithm for four circular strings.**

Index Terms—**fingerprint, mobile robot, consensus of circular strings, Hamming distance, genetic algorithms.**

I. Introduction

PROBLEMS of mobile robot visual navigation are extensively studied in contemporary robotics. In particular, we can mention the problem of sensor placement (see e.g. [1] – [4]), the problem of selection of a minimal set of visual landmarks (see e.g. [5], [6]), selection of partially distinguishable guards (see e.g. [7], [8]), the problem of placement of visual landmarks (see e.g. [9], [10]), visual calibration (see e.g. [12]), automatic generation of visual recognition modules (see e.g. [13]), systems of robot self-awareness (see e.g. [14] – [16]), the problem of anticipation of motion (see e.g. [17], [18]), localization problems (see e.g. [19]), etc.

Note that usage of systems of visual landmarks has been widely applied for mobile robot navigation (see e.g. [20]). There is a wide variety of different landmarks selection techniques. In particular, one-dimensional 360° panoramas received a lot of attention (see e.g. [21] – [29]).

Investigation of string processing problems has become essential in bioinformatics (see e.g. [30] – [34]). A number of efficient algorithms was proposed for solution of different hard string processing problems (see e.g. [35] – [39]). Note that many robotic methods consider images as strings of features and use different string matching algorithms to solve robotic problems (see e.g. [40] – [44]). In particular, the notion of fingerprint was proposed for creation unique identifiers for visually distinct locations (see [26]). Fingerprints are especially interesting when used within a topological localization (see e.g. [45]).

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Fig. 1. Neato XV-11 with camera.

A fingerprint is a circular string of features. The ordering of letters of a fingerprint matches the relative ordering of the features around the robot.

To create a fingerprint we need a 360° degrees panoramic image and a set of feature extractors that can identify significant features in the image. It is clear that the quality of feature extraction depends critically on the method of selection of the panoramic image.

Obviously, the panoramic image quality can be verified by human. However, for automatic generation of fingerprints, we need some algorithm of selection of the panoramic image. For instance, we use Neato XV-11 with camera (see [46] and Figure 1) to create a topological map for Kuzma-II.3 (see e.g. [10]). Note that Kuzma-II.3 is equipped with a 2 DOF robotic camera only.

We assume that Neato uses the laser sensor for exploration of the environment and laser map construction. For selected points of laser map, Neato constructs a sequence of panoramic images. This sequence gives us a set of fingerprints. After this, we need to solve the problem of selection of the consensus fingerprint (see e.g. Figure 2). For instance, the first three panoramas from Figure 2 were obtained by the robot. Since the other robot is present at each of these panoramas, no one of these panoramas can not be used for creating a landmark of high quality. However, we can use these panoramas for generation of some consensus panorama. The fourth panorama from Figure 2 gives us an example of a consensus panorama. We have created a fingerprint for each of the first three panoramas. Using this fingerprints we have

Fig. 2. Examples of panoramas.

created a consensus fingerprint. This consensus fingerprint allows us to generate a consensus panorama. In this paper, we consider some approaches to solve the problem of selection of the consensus fingerprint.

II. Preliminaries and Problem Definitions

Throughout the paper, the Hamming distance between S and T we denote by $D(S,T)$. Let

$$\Sigma = \{a_1, a_2, \dots, a_m\}$$

be a finite alphabet. As usual, the set of all nonempty strings over Σ we denote by Σ^+. We use $\mathcal{S}$ to denote the set

$$\{S_i \mid 1 \le i \le n, S_i \in \Sigma^+\}.$$

The length of a string S is the number of letters in it and is denoted as $|S|$. For simplicity, we use $S[i]$ to denote the ith letter in the string S, and $S[i,j]$ to denote the substring of S consisting of the ith letter through the jth letter. For given string S, let $\mathcal{C}(S)$ denote the set

$$\{S[i+1,|S|]S[1,i] \mid 1 \le i \le |S|\}$$

where $S[|S|+1,|S|]$ is the empty string.

The following are the problems we consider in this paper:

Center string problem (CS):

Instance: *A set $\mathcal{S}$ of strings each of length p, a positive integer k.*

Question: *Is there a string T of length p such that*

$$\max_{1\le i\le n} D(T,S_i) \le k?$$

Center circular string problem (CCS):

Instance: *A set $\mathcal{S}$ of strings each of length p, a positive integer k.*

Question: *Is there a string T of length p such that*

$$\max_{1\le i\le n} \min_{S\in\mathcal{C}(S_i)} D(T,S) \le k?$$

Center circular string with fixed letters problem (CCSFL):

Instance: *A set $\mathcal{S}$ of strings each of length p, a set Π of letters, $\Pi \subseteq \Sigma$, a positive integer k.*

Question: *Are there a string T of length p, a set*

$$\mathcal{S}' = \{S'_i \mid 1 \le i \le n\}$$

such that

- *for all $1 \le i \le n$,*

$$S'_i \in \mathcal{C}(S_i);$$

- *for each r if $S'_i[r] \in \Pi$, then*

$$S'_i[r] = S'_j[r],$$

where $1 \le i \le n$, $1 \le j \le n$;

- $$\max_{1\le i\le n} D(T,S'_i) \le k?$$

The idea of usage of solutions of problems CS, CCS, and CCSFL to generate a consensus panorama was first proposed in [11]. In particular, some experimental results for different mobile robots were presented in [11]. Also, it is shown in [11] that the usage of the problem CCSFL gives us significant advantage for large distances.

III. Complexity of CCS and CCSFL

Let Θ denote the set

$$\{b_1, b_2, \dots, b_{k+1}\}.$$

We use T_i to denote the set

$$S_i b_1 b_2 \dots b_{k+1},$$

for all $1 \le i \le n$. It is clear that there is T such that

$$\max_{1\le i\le n} \min_{S\in\mathcal{C}(T_i)} D(T,S) \le k$$

if and only if there is U such that

$$\max_{1\le i\le n} D(U,S_i) \le k.$$

Note that CS is **NP**-complete (see e.g. [47]). Therefore, CCS is **NP**-complete.

In the special case $\Pi = \emptyset$, CCSFL becomes CCS. So, CCSFL is **NP**-complete.

IV. An explicit reduction from CCS to the satisfiability problem

In view of **NP**-completeness of CCS, we need some efficient algorithm to solve the problem. Encoding hard problems as instances of the satisfiability problem and solving them with efficient satisfiability algorithms has caused considerable interest recently (see e.g. [48] – [54]). Now we consider an explicit reduction from CCS to the satisfiability problem.

Let

$$\varphi[1] = \bigwedge_{1\le i\le n} \bigvee_{1\le j\le p} x[i,j],$$

$$\varphi[2] = \bigwedge_{\substack{1\le i\le n,\\ 1\le j[1]<j[2]\le p}} (\neg x[i,j[1]] \vee \neg x[i,j[2]]),$$

$$\varphi[3] = \bigwedge_{1\le i\le p} \bigvee_{1\le j\le m} y[i,j],$$

$$\varphi[4] = \bigwedge_{\substack{1\le i\le p,\\ 1\le j[1]<j[2]\le m}} (\neg y[i,j[1]] \vee \neg y[i,j[2]]),$$

$$\varphi[5] = \bigwedge_{\substack{1\le i\le n,\\ 1\le j\le p-k}} \bigvee_{1\le s\le p} z[i,j,s],$$

$$\varphi[6] = \bigwedge_{\substack{1\le i\le n,\\ 1\le j\le p-k,\\ 1\le s[1]<s[2]\le p}} (\neg z[i,j,s[1]] \vee \neg z[i,j,s[2]]),$$

$$\varphi[7] = \bigwedge_{\substack{1\le i\le n,\\ 1\le j[1]<j[2]\le p-k,\\ 1\le s\le p}} (\neg z[i,j[1],s] \vee \neg z[i,j[2],s]),$$

$$\varphi[8] = \bigwedge_{\substack{1\le i\le n,\\ 1\le j\le p-k,\\ 1\le s\le p,\\ 1\le t\le m,\\ 1\le r\le p,\\ S_i[1+(s+r-1 \bmod p)]\ne a_t}} (\neg z[i,j,s] \vee \neg y[s,t] \vee \neg x[i,r]),$$

$$\xi = \bigwedge_{i=1}^{8} \varphi[i].$$

It is not hard to verify that ξ is satisfiable if and only if there is a string T of length p such that $\max_{1\le i\le n} \min_{S\in\mathcal{C}(S_i)} D(T,S) \le k$. It is clear that ξ is a CNF. Using standard transformations we can easily obtain an explicit transformation ξ into ζ such that $\xi \Leftrightarrow \zeta$ and ζ is a 3-CNF. It is clear that ζ gives us an explicit reduction from CCS to 3SAT.

V. Experimental setup

We have designed a set of natural instances for CCS. In particular, we use Neato XV-11 with camera to obtain panoramas of different environments. We create fingerprints for these panoramas. It should be noted that thresholding-based techniques have been widely used in image segmentation (see e.g. [55]). In particular, we consider edges and color features as the set of features (see [26]). To detect such features we use histogram based edge detection, color patches detection, and fuzzy voting scheme (see [26]).

It should be noted that the colors in the scene are not known in advance. In particular, the colors can cover the entire color space. We need to reduce the quantity of different color patches and memory space. Therefore, similar colors are grouped together considering their hue. Following [26], we can use a fuzzy voting scheme for this purpose. In particular, we can use some saturation thresholding. After this, each pixel in the image will add a value depending on the hue. For this purpose, we need some window filter. In particular, $\{1,2,3,2,1\}$ and $\{1,2,2,2,1\}$ are considered in [26]. In general, we can not use some fixed window filter to obtain fingerprints. Therefore, we consider the set of window filters

$$\{\{x_1,x_2,\dots,x_k\} \mid 5\le k\le 11, 1\le x_i\le 10, 1\le i\le k\}$$

and use a simple genetic algorithm that evolves this set to select proper window filter.

We have used heterogeneous cluster (500 calculation nodes, Intel Core i7). Each test was runned on a cluster of at least 100 nodes.

VI. SAT solvers for CCS

To obtain optimal solutions of CCS we use genetic algorithms OA[1] (see [9]), OA[2] (see [38]), OA[3] (see [52]), OA[4] (see [56]), and OA[5] (see [57]) for the satisfiability problem. Also, we have considered GSAT with adaptive score function (see [58]). Selected experimental results are given in Table I.

TABLE I
EXPERIMENTAL RESULTS FOR DIFFERENT GENETIC ALGORITHMS

time	average	maximum	best
OA[1]	17.9 min	1.27 hr	2.2 min
OA[2]	16.1 min	1.56 hr	1.3 min
OA[3]	3.43 min	34 min	11 sec
OA[4]	14.9 sec	29.15 sec	3.3 sec
OA[5]	5.87 sec	21.85 sec	0.8 sec
GSAT	4.76 min	18.19 min	1.13 min

VII. APPROXIMATE GENETIC ALGORITHMS FOR CCS

For real-time navigation robots require fast algorithms. Quite often, the performance of SAT-solvers for CCS is insufficient for such purposes. Therefore, it is natural to consider the problem of finding approximate algorithms for CCS.

At first, we consider a relatively standard genetic algorithm GA[1] for solution of CCS. Let $\mathcal{S}$ be a collection of strings over Σ. We assume that

$$\mathcal{T} = \{T_s\tau_{1,s}\tau_{2,s}\dots\tau_{n,s} \quad | \quad 1 \le s \le r, \; T_s \in \Sigma^+, \; \tau_{i,s} \in \{1,2,\dots,p\}\}$$

is a set of potential solutions of CCS for $\mathcal{S}$ where T_s is a potential consensus string and $\tau_{i,s}$ defines rotation of S_i. We consider $\mathcal{T}$ as a set of individual chromosomes. The fitness function of GA[1] is

$$\max_{1\le i\le n} D(T_s, S_i[\tau_{i,s}+1,p]S_i[1,\tau_{i,s}]).$$

We assume that $\lceil \frac{r}{2} \rceil$ chromosomes of the existing population is selected to breed a new generation. Chromosomes are selected by the fitness function. It is clear that two parent chromosomes can be represented in the following form:

$$T_{s[1]}\tau_{1,s[1]}\tau_{2,s[1]}\dots\tau_{n,s[1]},$$

$$T_{s[2]}\tau_{1,s[2]}\tau_{2,s[2]}\dots\tau_{n,s[2]}.$$

In this case, two child chromosomes

$$T_{s[1]}[1,q[1]]T_{s[2]}[q[1]+1,p]\tau_{1,s[1]}\tau_{2,s[1]}\dots$$

$$\tau_{q[2],s[1]}\tau_{q[2]+1,s[2]}\tau_{q[2]+2,s[2]}\dots\tau_{n,s[2]},$$

$$T_{s[2]}[1,q[1]]T_{s[1]}[q[1]+1,p]\tau_{1,s[2]}\tau_{2,s[2]}\dots$$

$$\tau_{q[2],s[2]}\tau_{q[2]+1,s[1]}\tau_{q[2]+2,s[1]}\dots\tau_{n,s[1]}$$

can be defined by two random numbers $q[1]$ and $q[2]$. We consider random variations of values of $\tau_{i,s}$ as mutations.

Also, we consider a genetic algorithm GA[2] to evolve a set of functions

$$G = \{g_i(x_1,x_2) \mid i \in I\}$$

where

$$g_i : \{1,2,\dots,n\} \times \{1,2,\dots,p\} \to \{1,2,\dots,p\}.$$

We can consider g_i as a mutation for GA[1]. Note that optimal solutions of CCS can be obtained using satisfiability algorithms. An optimal solution for $\mathcal{S}$ we denote by

$$T_{opt}.$$

We can apply G to GA[1] and obtain some solution T. The standard edit distance between T_{opt} and T we denote by

$$E(T_{opt}, T).$$

We consider

$$\frac{1}{E(T_{opt},T)+1}$$

as the fitness function of GA[2].

Let GA[3](t) be a genetic algorithm GA[1] with the set of mutations G after t generations of GA[2]. For genetic algorithms GA[1] and GA[3](t), we consider the average value of

$$\frac{|T|}{|T_{opt}|}$$

as a rate of the quality of the genetic algorithm. Selected experimental results for different approximate genetic algorithms for CCS are given in Tables II, III.

TABLE II
QUALITY OF GENETIC ALGORITHMS FOR DIFFERENT NUMBERS OF GENERATIONS

	10^2	10^3	10^4	10^5	10^6
GA[1]	3.69	3.21	2.84	2.39	2.11
GA[3](10^3)	2.47	2.08	1.73	1.52	1.46
GA[3](10^4)	2.37	1.12	1.07	1.06	1.052

TABLE III
PERFORMANCE OF GENETIC ALGORITHMS FOR DIFFERENT NUMBERS OF GENERATIONS

time	average	maximum	best
GA[1]	0.219 sec	0.244 sec	0.197 sec
GA[3](10^3)	0.527 sec	0.556 sec	0.438 sec
GA[3](10^4)	0.331 sec	0.349 sec	0.312 sec

VIII. THE PROBLEM CCS FOR FOUR CIRCULAR STRINGS

The set of edges $\{b_1, b_2, \dots, b_{m[1]}\}$ we denote by Σ_1. The set of color features $\{c_1, c_2, \dots, c_{m[2]}\}$ we denote by Σ_2. We assume that

$$\Sigma = \Sigma_1 \cup \Sigma_2.$$

The set

$$\{F_i \mid 1 \le i \le q, F_i \in \Sigma^+\}$$

of fingerprints of given point of the environment we denote by F. A number of occurrences of string u in string v we denote by

$$\#occ(u,v).$$

TABLE IV
THE AVERAGE NUMBER N OF CORRECT PREDICTIONS FOR DIFFERENT NUMBERS OF GENERATIONS

number of generations	10^2	10^3	10^4	10^5	$5 \cdot 10^5$	10^6	$5 \cdot 10^6$	10^7	$5 \cdot 10^7$	10^8	$5 \cdot 10^8$
N	53 %	56 %	58 %	73 %	77.3 %	81 %	84.4 %	87 %	88.7 %	89.2 %	89.3 %

A function

$$\sum_i \alpha_i \sum_j^q \#occ(u_i, F_j)$$

we denote by $H(F)$.

Note that CCS can be solved by an $O(n^2 \text{log} n)$-time algorithm for three circular strings and an $O(n^3 \text{log} n)$-time algorithm for four circular strings [59]. We assume that if $H(F) < 1$, then we can use the algorithm for four circular strings.

To find values of α_i and u_i we use a genetic algorithm GA[4]. Note that GA[4] evolves a population of sets

$$\{\alpha_i, u_i \mid \alpha_i \in Q, u_i \in \Sigma_1, i \in I\}.$$

We assume that initial value of the fitness function f is equals to 1 for any set. We use satisfiability algorithm to obtain optimal solution for F. An optimal solution for F we denote by T_{opt}. Let T denote the solution that obtained by the algorithm for four circular strings [59]. Let

$$k[1] = \max_{1 \le i \le q} \min_{S \in \mathcal{C}(F_i)} D(T_{opt}, S),$$

$$k[2] = \max_{1 \le i \le q} \min_{S \in \mathcal{C}(F_i)} D(T, S).$$

For given set of values of α_i and u_i, we assume that

$$f_{new} = \begin{cases} f_{old} + 1, & \text{if} \quad k[1] \ge 0.9k[2] \quad \text{and} \quad H(F) < 1, \\ f_{old} + 1, & \text{if} \quad k[1] < 0.9k[2] \quad \text{and} \quad H(F) \ge 1, \\ f_{old} - 1, & \text{if} \quad k[1] \ge 0.9k[2] \quad \text{and} \quad H(F) \ge 1, \\ f_{old} - 1, & \text{if} \quad k[1] < 0.9k[2] \quad \text{and} \quad H(F) < 1. \end{cases}$$

Selected experimental results are given in Table IV.

IX. THE GENERAL SCHEME OF THE ALGORITHM FOR THE PROBLEM OF SELECTION OF THE CONSENSUS FINGERPRINT

For set F of fingerprints of given point of the environment if $H(F) < 1$, then we use the algorithm for four circular strings [59]. If $H(F) \ge 1$, we try to solve CCSFL.

Let C_i be the longest subsequence of F_i such that

$$C_i \in \Sigma_1^+,$$

where $1 \le i \le q$. Frequently, we have

$$C_i = C_j,$$

for all $i, j \in \{1, 2, \ldots, q\}$. Moreover, in many cases, the value of

$$\max_{1 \le i \le q} \{t - s \mid s < r < t, \; F_i[s] \in \Sigma_1, \; F_i[t] \in \Sigma_1, \; F_i[r] \in \Sigma_2\}$$

is relatively small. Under these conditions, we can reduce CCSFL to CS with small value of p. If we can not use the algorithm for four circular strings or solve CCSFL, we use GA[3](10^4).

For the general approximate algorithm for the problem of selection of the consensus fingerprint, we have obtained following results: average time – 0.117 sec; maximum time – 0.643 sec; best time – 0.057 sec.

X. CONCLUSION

In this paper, we have proposed an approach to solve the problem of selection of the consensus fingerprint. In particular, we have used histogram based edge detection, color patches detection, and fuzzy voting scheme. For fuzzy voting scheme, we have applied different window filters. To select proper window filter a simple genetic algorithm have used. We have used for selection of the consensus fingerprint the center string problem, the center circular string problem, and the center circular string with fixed letters problem.

We have considered an efficient algorithm for solution of CCS. In particular, we have proposed an explicit reduction from CCS to the satisfiability problem. To obtain optimal solutions of CCS we have used different genetic algorithms for the satisfiability problem. We have proposed genetic algorithms for approximate solution of CCS. Also, we have considered an approach for solution of CCS for four circular strings.

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