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String Shape Recognition Using Enhanced Matching Method From 3D Point Cloud Data

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Abstract— **The deformable object such as string, cloth and paper, is soft and can change its shape easily. It is difficult for a robot to manipulate deformable object because it needs to deal with various shape. For the operation of deformable object, it is important to recognize the shape of them. In our previous research, point chain model and the string shape recognition method were proposed. Point chain model is a structure to describe a string shape by a series of connections of points. And the string shape recognition method are algorithms to recognize a string shape from 3D point cloud data and output point chain model. However, the previous method sometimes occurred misrecognition of segments. Therefore, enhanced matching method is proposed to improve recognition performance.**

I. INTRODUCTION

There are many deformable objects such as cloth, paper and string around our living space. The deformable object is soft and can change its shape easily. It is difficult for a robot to manipulate a deformable object because a robot needs to deal with various shape. The demand of manipulation of deformable object is growing.

In recent years, the cellular manufacturing system which cope with multi-kind and small quantity production is increasing. In this manufacturing system, many types of robots are working. But it still remains many operations which failed to be automated. For example, it is expected to automate the wiring operation [1]. If robots work in people living space, there many deformable objects such as string and cloth. So they have to manipulate these deformable objects on housework [2] [3].

Our research group has been focusing on the shape operation of a string. There are three steps in the operation of a string. The first step is recognition of a string shape. To realize operations of a string, it is necessary to feedback shape information to robot manipulator. String shape recognition algorithms using camera image are proposed in some studies [4] [5]. The second step is planning for string shape operations. The description structure called P-data to represent a string shape is mentioned in [5] [6]. P-data is composed of abstracted elements such as end, node and segment, and these relation are represented by a matrix. The third step is to calculate a trajectory of robot manipulator. The methods to calculate a trajectory of robot are proposed in some paper [7] [8]. There are some studies [8] [9], which realized knotting operation of a string using camera image.

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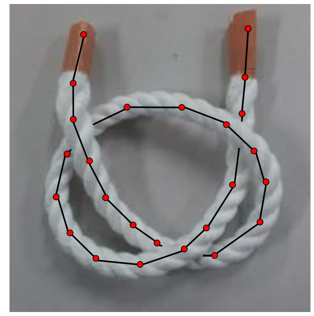


Fig. 1. Point chain model

In our previous study [10], point chain model was adopted to describe a string shape. Point chain model is a data structure that describes a string shape by a series of connections of points as shown in Fig. 1. The string shape recognition method was also proposed to recognize a string shape from 3D point cloud data. Point chain model is generated by this method. There are two advantage of this method. One is to acquire whole shape data without occlusion by using techniques to process point cloud data such as ICP. The other is to compress the information of a lot of points representing surface of objects. In the string shape recognition method, matching method is core algorithm to recognize a string shape. However, matching method had a problem that misrecognition sometimes occurs at intersection. Therefore, the enhanced matching method is proposed to solve misrecognition. In this paper, in addition, reconstruction algorithm of point chain model is proposed. The purpose of this algorithm is to recognize a whole string shape correctly.

II. OVERVIEW OF SHAPE RECOGNITION

Fig. 2 shows the flowchart of the string shape recognition method. This method outputs point chain model from 3D point cloud data. The core algorithm of shape recognition is matching method. This algorithm is specialized to extract point chain model from long and thin linearly arranged points. In the string shape recognition method, processes excluding matching method are preprocess for better performance of matching method.

A. Obtaining 3D Point Cloud Data

3D point cloud data of a string is obtained by a distance camera. A target object and an experimental environment are shown in Fig. 3. The radius r of this string is approximately 4.2[mm], and its length is approximately 400[mm]. Point cloud data of the target object are obtained from eight

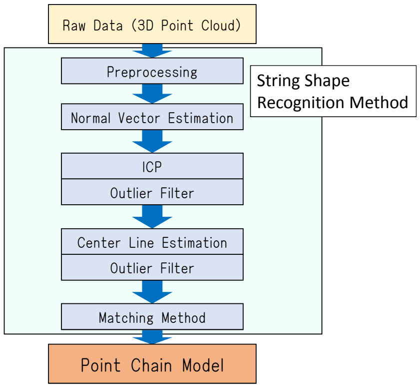


Fig. 2. Flowchart of the string shape recognition method

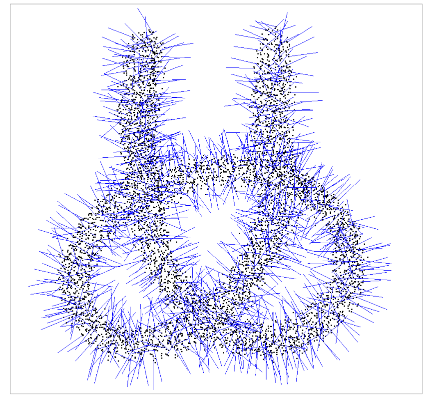


Fig. 4. Combined point cloud with nv

different viewpoints to suppress camera occlusion. These point cloud data are defined as raw point cloud.

B. Preprocessing

Raw point cloud obtained by distance camera includes non-target objects such as floor and experimental equipments. Therefore, these unnecessary points must be removed from raw point cloud. Here, a threshold for z_w is set as 5[mm]. Points that have lower value than the threshold on z_w direction are removed from raw point cloud. Processed point cloud data is defined as target point cloud.

C. Statistical Outlier Filter

Point cloud data includes undesirable points called outlier. Statistical outlier filter can remove outlier based on distance to neighbor points [11]. This process is used after each algorithm to remove unnecessary data.

D. Normal Vector Estimation

Normal vector is perpendicular to given plane. Normal vector estimation [12] is an algorithm to calculate normal vector of each point in point cloud data. In this algorithm, Principle Component Analysis (PCA) is applied to local point cloud, which is made up of a target point and its neighbor points. Normal vector can be calculated by eigenvalue analysis of covariance matrix. The information of normal vector is prepared for next process.

Each point in processed point cloud has a normal vector. Therefore, this point cloud data is defined as point cloud with NV(Normal Vector).

E. Iterative Closest Point (ICP)

ICP is an algorithm to minimize the difference between two point clouds [13] [14]. Two point clouds obtained from different viewpoints are combined by using ICP algorithm. Point cloud with NV obtained from different viewpoints are combined into one point cloud data without camera occlusion. Outlier filtered point cloud data processed by ICP is defined as combined point cloud with NV, which is shown in Fig. 4.

F. Center Line Estimation

Next, an algorithm to estimate center line of a string is described. This algorithm has an effect of thinning point cloud, and improves the recognizability of matching method. Because matching method is an algorithm that is specialized to extract point chain model from long and thin linearly arranged points.

Here, $\boldsymbol{c}_i$ is a point that is assumed to be on the center line of a string. As shown in Fig. 5 (a), $\boldsymbol{c}_i$ should exist at the position that is moved string radius r to the opposite direction of $\boldsymbol{n}_i$ from $\boldsymbol{p}_i$. This relationship is represented by Eq.(1)

$$\boldsymbol{c}_i = \boldsymbol{p}_i - r \cdot \boldsymbol{n}_i. \tag{1}$$

However, actual normal vector $\boldsymbol{n}_i$ is not accurate. Therefore, points which exist within $2r$ from $\boldsymbol{p}_i$ are extracted as shown in Fig. 5 (b). The number of collected points is $\bar{N}_i$,

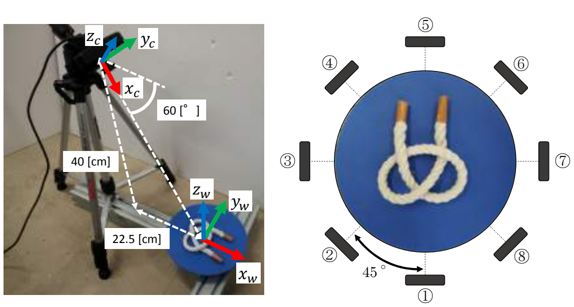
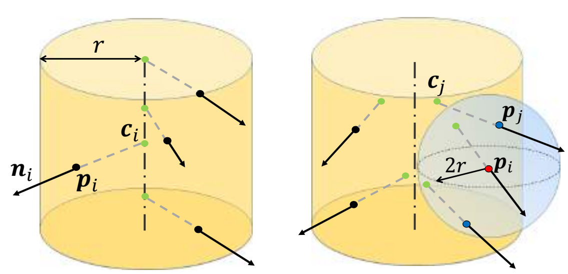


Fig. 3. A target object and an experimental environment



(a) Original (b) Improved

Fig. 5. Center line estimation

Fig. 6. Center line point cloud

and J_i is defined as a set of point number of each neighbor point. Here, $\bar{\boldsymbol{c}}_i$ is calculated by Eq.(2)

$$\bar{\boldsymbol{c}}_i = \frac{1}{\bar{N}_i} \sum_{j \in J_i} \boldsymbol{c}_j. \tag{2}$$

$\bar{\boldsymbol{c}}_i$ are robust against measurement error and outlier because position of neighbor $\boldsymbol{c}_i$ are averaged. Outlier filtered point cloud $\bar{\boldsymbol{c}}_i$ is defined as center line point cloud. Fig. 6 shows center line point cloud.

G. Matching Method

Matching method is an algorithm specialized to extract point chain model from long and thin linearly arranged points. The feature of this algorithm is to utilize double sphere search areas, which are centered on the target point in center line point cloud as shown in Fig. 7. The radius of inner search sphere is r_n, that of outer search sphere is r_f. The process flow is as follows.

1) Double search sphere are made centered on the target point as shown in Fig. 7 (a).
2) Points which exist within r_n from the target point are eliminated from this process, and can not be connected as shown in Fig. 7 (b).

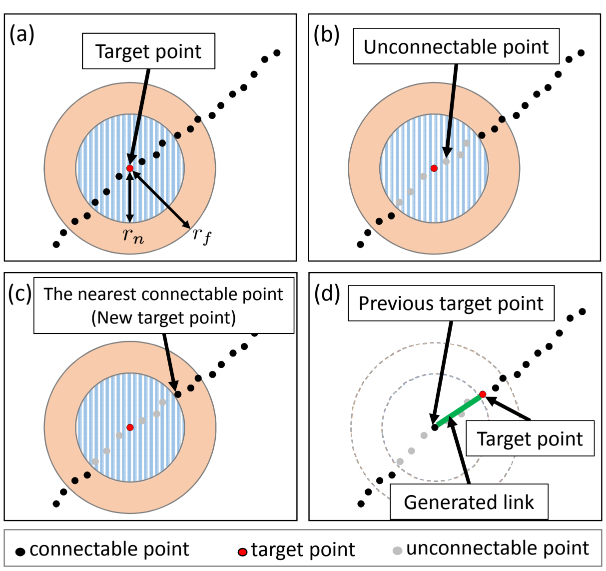


Fig. 7. The process of matching method

3) If there are no connectable point inside of r_f, the sequence finishes.
4) The nearest connectable point which exists within r_f from the target is found, then new link from the target point to this point is generated as shown in Fig. 7 (c).
5) Linked point becomes next target point as shown in Fig. 7 (d).
6) Return to process 1).

These sequences repeat until all points in center line point cloud are unconnectable.

III. Enhanced Matching Method

A. Misrecognition of A String Shape

Matching method is an algorithm specialized to extract point chain model from long and thin linearly arranged points. However, width of linearly arranged points tends to grow around an intersection because two pieces of linearly arranged points cross as shown in Fig. 8 (b). Parts of point cloud around intersection are not suitable to be proceeded by matching method. Therefore, in enhanced matching method, shape recognition in intersection is not conducted. Instead a process for finding restart points of matching method is conducted. A series of these processes is defined as bifurcated restart.

B. Thinning of Point Cloud

Thinning of point cloud is a process to thin center line point cloud for better performance of next process. Here, $\boldsymbol{p}_i (i = 1, 2, \cdots, N)$ is a point in center line point cloud, and $\boldsymbol{q}_j (j = 1, 2, \cdots, n_i)$ are neighbor points of $\boldsymbol{p}_i$ which have less distance from $\boldsymbol{p}_i$ than r_c. A point $\boldsymbol{a}_i$ in point cloud made by this process is calculated by Eq.(3)

$$\boldsymbol{a}_i = \frac{1}{n_i} \sum_{j=1}^{j} \boldsymbol{q}_j. \tag{3}$$

Generated point cloud data is defined as thinned point cloud. Fig. 9 shows thinned point cloud under the condition where r_c is 4.2×10^{-3}[m].

C. Distinction of Intersection

It needs to distinguish intersection from other point cloud in enhanced matching method. In intersection, width of linearly arranged points tends to grow because two pieces of linearly arranged points are crossed. Therefore, PCA

(a) Actual string shape (b) Center line point cloud (c) Point chain model

Fig. 8. Misrecognition of a string shape

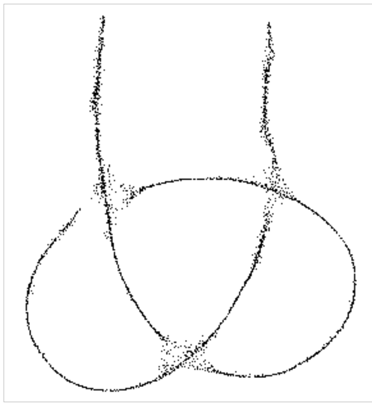


Fig. 9. Thinned point cloud

is applied to local point cloud so as to contribution rate of main axis of covariance matrix. That is defined as an indicator which evaluate the aspect ratio of neighbor points. Here, $\boldsymbol{p}_i (i = 1, 2, \cdots, N)$ is a point in thinned point cloud, $\boldsymbol{q}_j (j = 1, 2, \cdots, n_i)$ are its neighbor points which exist within r_s from $\boldsymbol{p}_i$. The average point $\boldsymbol{q}_a$ of neighbor points $\boldsymbol{q}_j$ is defined as Eq.(4).

$$\boldsymbol{q}_a = \frac{1}{k} \sum_{j=1}^{k} \boldsymbol{q}_j \tag{4}$$

And the covariance matrix $\boldsymbol{R}$ is calculated from this local point cloud $\boldsymbol{q}_j$ by Eq.(5)

$$\boldsymbol{R} = \frac{1}{k} \sum_{j=1}^{k} \{(\boldsymbol{q}_j - \boldsymbol{q}_a)(\boldsymbol{q}_j - \boldsymbol{q}_a)^T\}. \tag{5}$$

Next, eigenvalues and eigenvector of the covariance matrix are calculated. These are important to calculate contribution rate. The correlation of local point cloud data can be calculated by using PCA. Eigenvector of the covariance matrix are called principle component, which represent axes of correlation. And eigenvalues of the covariance matrix represent contribution of each axis. Here, eigenvalues of point cloud are defined as λ_1, λ_2 and λ_3 in sequence of decreasing order of absolute value. Then, contribution rate

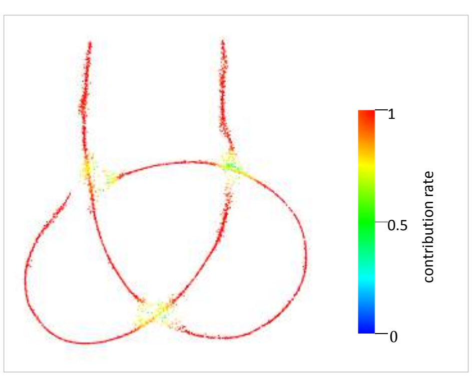


Fig. 10. Contribution rate ρ_i : the red points indicate intersection point

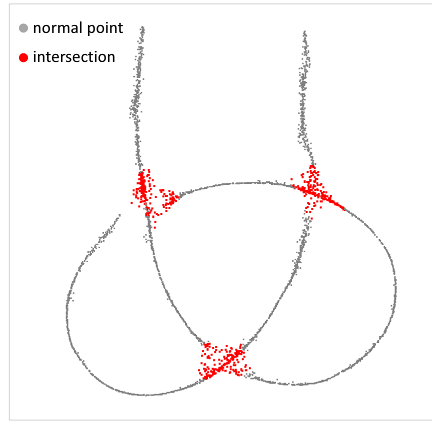


Fig. 11. Points which constitute intersection

ρ_i of $\boldsymbol{p}_i$ is defined as Eq.(6).

$$\rho_i = \frac{|\lambda_1|}{|\lambda_1| + |\lambda_2| + |\lambda_3|} \tag{6}$$

The contribution rate under the condition where r_s is 4.2×10^{-3}[m] is illustrated in Fig. 10.

When contribution rate is smaller, it indicated that the point has higher possibility to belong intersection. Points which constitute intersection are distinguished using contribution rate. Here, the threshold of contribution rate is defined as ρ_t. Points which have less contribution rate than ρ_t are distinguished as in intersection. Fig. 11 shows the result under the condition where ρ_t is 0.9.

D. Bifurcated Restart

In enhanced matching method, shape recognition in intersection is not conducted. Instead, a process called bifurcated restart is conducted. In this process, points around an intersection are eliminated from shape recognition. Next, restart points of matching method is found.

1) Detection of Intersection: Considering the case in which the search spheres of matching method goes through an intersection as shown in Fig. 12. It is expected that the closer the search spheres get to an intersection, the more the ratio of intersection points included in neighbor points will rise. Here, n_n is the number of points which exist in outer search sphere. n_c is the number of intersection point which exist in outer search sphere. The rate R_c of the number of

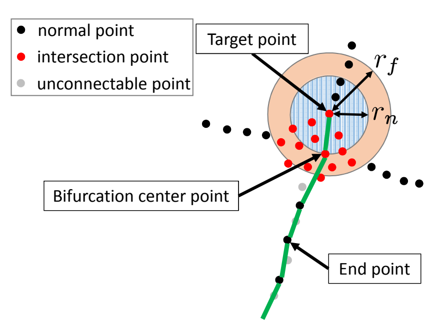


Fig. 12. A intersection and double search sphere

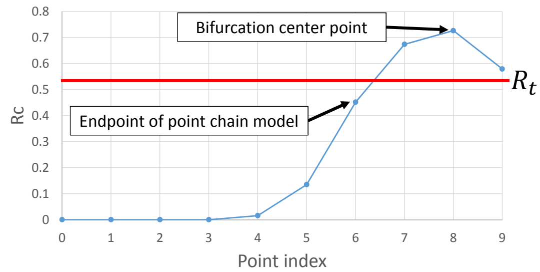


Fig. 13. The transition of R_c

intersection points to that of neighbor points is defined as Eq.(7).

$$R_c = \frac{n_c}{n_n} \tag{7}$$

The transition of R_c is expected as Fig. 13. Therefore, a threshold R_t for R_c is defined. If a point with R_c which be local maximum and be more than R_t is found, the point is set as bifurcation center point. When R_c of certain point exceeds R_t at first time, the previous point of that is set as endpoint of point chain model.

2) Finding Restart Points: Restart points of matching method need to be found to construct whole string shape. Fig. 14 indicates the process to find restart points. Here, double search sphere centered on the bifurcation center point are set. As shown in Fig. 14 (a), radius of inner search sphere is defined as r_{cn}, and that of outer search sphere is defined as r_{cf}. Points which exist in r_{cn} are eliminated from this process, and cannot be connected. The processes to find restart points are as follows.

1) If there are no connectable point which exist within r_{cn} from the bifurcation center point, the sequence finishes.
2) If the nearest connectable point which exists within r_{cf} from the bifurcation center point is found, then this point is set as restart point of matching method as shown in Fig. 14 (b).
3) Double search sphere centered on the restart point are set. The radius of inner search sphere is r_n, that of outer search sphere is r_f as shown in Fig. 14 (c).
4) Points which exist within r_n from the restart point are eliminated from shape recognition process, and cannot be connected as shown in Fig. 14 (c).
5) The nearest connectable point which exists within r_f from the restart point is found, and new link to this point is generated as shown in Fig. 14 (d).
6) Return to process 1).

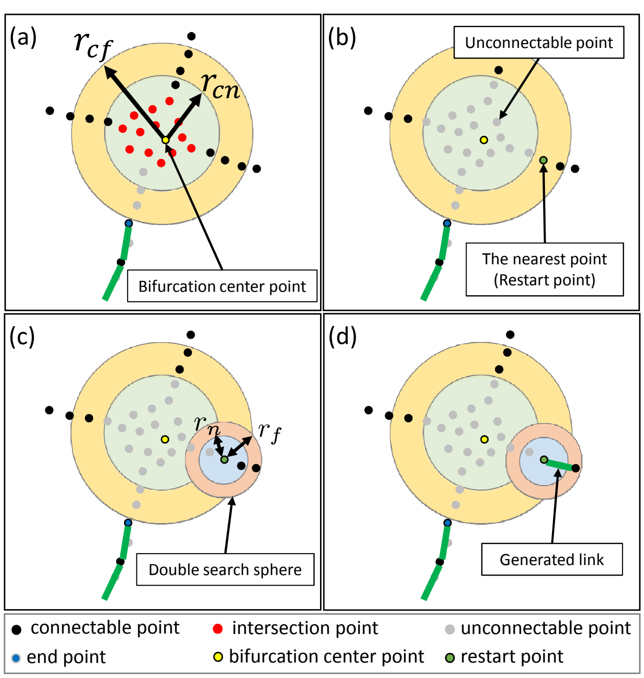


Fig. 14. The process of bifurcated restart

TABLE I

SETTING OF PARAMETERS

Parameter	Value	Recommended condition
R_t	0.7	$R_t < 1$
r_n	4.2×10^{-3}[m]	$0 < r_n$
r_f	8.4×10^{-3}[m]	$r_n < r_f$
r_{cn}	12.6×10^{-3}[m]	$(r_n + r_f) \leq r_{cn}$
r_{cf}	14.7×10^{-3}[m]	$r_{cn} < r_{cf} < (r_{cn} + r_n)$

After this process, new matching method sequences start from each restart point.

There are some parameters in this method. Table I shows the value and recommended condition of each parameter. R_t was heuristically set. r_n and r_f were set on basis of string radius r. r_{cn} and r_{cf} were set based on the actual size of string intersection. The result of enhanced matching method is shown in Fig. 15.

E. Reconstruction of Point Chain Model

1) Reconnection of Close Endpoints: There are some short segments in generated point chain models. Therefore, close endpoints of each segment should be reconnected, in order to make sequential point chain model. A couple of endpoints which have less distance than r_f are connected. The result is shown in Fig. 16.

2) Connection of point chain model at intersection: Endpoints which gather around an intersection are connected

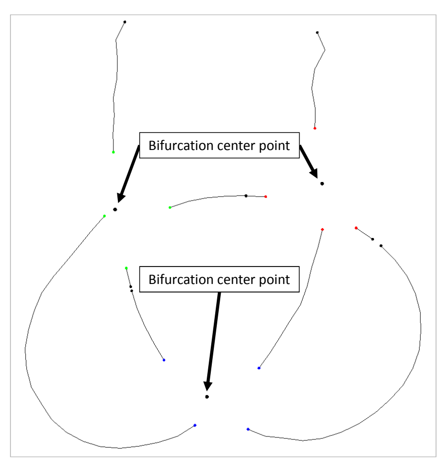


Fig. 15. The result of enhanced matching method

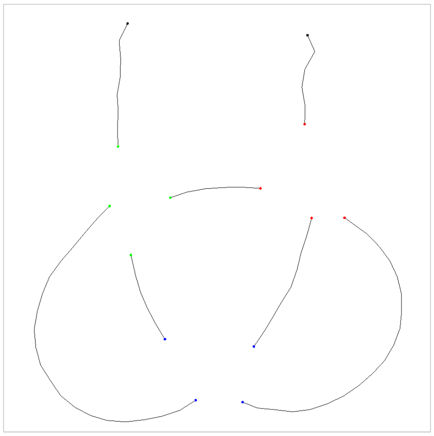


Fig. 16. The result of conjugation

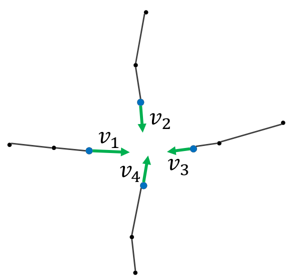


Fig. 17. Four endpoints which gather around an intersection

correctly by this process. Fig. 17 shows four endpoints which gather around an intersection. In Fig. 17, each arrowed line drawn from endpoints means direction of them. Two end points that have opposite direction should be connected. Here, end direction vector $\boldsymbol{v}_i(i \in I : 1, \cdots, 4)$ are defined. In addition, the evaluation value b is defined as Eq.(8).

$$b(j,k,l,m) = \boldsymbol{v}_j \cdot \boldsymbol{v}_k + \boldsymbol{v}_l \cdot \boldsymbol{v}_m \quad (j,k,l,m \in I) \tag{8}$$

Inner product of $\boldsymbol{v}_i$ that have opposite direction takes value close to -1. Therefore, the combination of endpoints couple which has minimum evaluation value b in all combinations is regarded as feasible connection. The result of connection according to evaluation is shown in Fig. 18. In Fig. 18, camera icons mean viewpoints, and intersections viewed from each viewpoint are shown in right half of Fig. 18. As show in each image, a string shape in intersection is correctly reconstructed by this algorithm.

IV. CONCLUSIONS

The enhanced matching method and reconstruction algorithm are proposed to recognize correct string shape in this paper. In enhanced matching method, a process called bifurcated restart occurs at an intersection. Intersection is detected using the contribution rate which are calculated by using PCA. In addition, output point chain model is correctly repaired by reconstruction algorithms. By the string shape recognition method using enhanced matching method, a simply shaped string can be recognized correctly. Some parameters of enhanced matching method were set heuristically. Therefore, these parameters should be adjusted logically

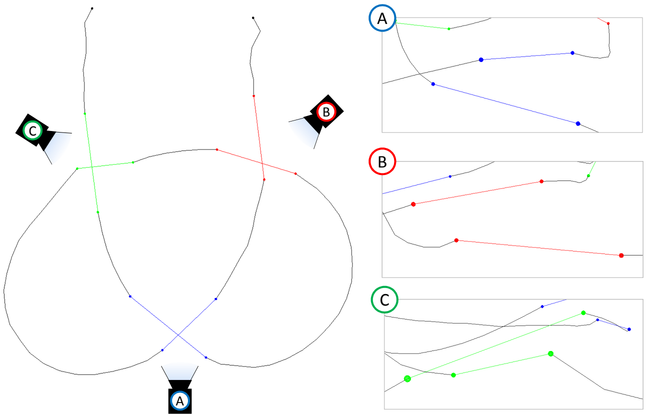


Fig. 18. Recognized point chain model with correct connections

for better performance. Additional experiment to evaluate proposed method should be conducted.

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