## **Computational Design and Fabrication of Hanging Structures**

Supplemental Material

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## **1 VARIABLE DEFINITIONS**

In this section we list all variables and their definitions in the paper (Table.1). These symbols are generic in both the description of our method and the pesudocode below (Alg.1).

Symbol	Definition
N	number of rods
mi	mass of rod <i>i</i>
li	length of rod <i>i</i>
$\vec{M}$	the N-dimensional mass vector of all rods
Ĺ	the N-dimensional length vector of all rods
$\theta_i$	the angles of the rod <i>i</i> relative to the horizontal plane
Θ	the N-dimensional angle vector of all rods
$\phi_{i,i+1}$	the angle between rod $i$ and rod $i + 1$
u	number of geometry parameters
Ĝ	the geometry parameter vector of all rods
ртi	the $i^{th}$ junction of target shape $T$
₽Si	the $i^{th}$ junction of simulation shape $S$
Yj	particle <i>j</i> in PSO algorithm
$\gamma_j^k$	the position of particle $\gamma_j$ in the $k^{th}$ iteration, which is a configuration vector
$\Gamma_j^k$	a angle vector, i.e. the simulation result of a configuration $P_j^k$
$\widetilde{D}$	the Euclidean distance between two curve
$\vec{D}_j^k$	the weighted sum of the deviation vector, i.e. the directed distance between the junction points
$\gamma_{lj}^k$	the <i>local best</i> position of particle $j$ in the $k^{th}$ iteration
$\gamma_g^k$	the <i>global best</i> position of whole swarm in the $k^{th}$ iteration
Y <sup>k</sup> <sub>bj</sub>	the <i>better</i> position for particle $j$ in the $k^{th}$ iteration
$\gamma_{wj}^k$	the <i>worse</i> position for particle $j$ in the $k^{th}$ iteration

**Table 1: Variable definitions** 

## 2 THE IMPROVED PSO ALGORITHM

Given a user-specified shape  $\vec{\Theta}$ , our configuration optimization algorithm will find an optimal configuration  $(\vec{M}, \vec{G})$  to form the target shape.

We solve this non-linear problem by a improved-particle swarm optimization(PSO) algorithm. Compared with the original PSO algorithm, we apply two more guide points called the *better solution* point and the *worse solution* point, while keeping the two original points, i.e. the *local best* point and the *global best* point. Alg.1 shows the pseudocode of our algorithm.

Here function *simulateShape()* is the shape simulation algorithm given in Chapter4.1 in the paper.

Function *selectionPrinciple(*) serve to provide the *better* and *worse* position for current particle according to deviation directions  $\vec{D}$ . In Fig.1, yellow arrow indicates the deviation direction bwtween target shape(green) and the current simulation shape(red), which is applied as the error descriptor in our work. The direction vector is the sum of all blue vectors.

The selection principles have been described in the paper, but for getting a clearer understanding of the principles, we list several typical cases in the form of diagrams(Fig.2 and Fig.3).



Figure 1: Deviation direction.



Figure 2: A typical *worse* condition. Here, the target shape is shown in orange. The shape in red is a *worse* shape than current one (blue).



Figure 3: Two better conditions. Here, the shapes in green are better shape than current one (blue).

## 3 ALGORITHM PERFORMANCE

Table2 demonstrate the performance of our improved PSO algorithm in some typical cases. We can see that the calculation cost is directly related to the complexity of target structures. The polygon configuration optimization cost more time before converging than Semi-circle and triangle. This is because the optimal solution is almost located on the boundary of search-space, so the particles can hardly know the information of the optimal solution. But over all, the time-consuming of our method is acceptable.

Target shape	Number of rods	Iteration number	Consuming- time(s)
	8	7	6.217
Semi-circle	12	17	37.251
	20	21	143.171
	8	8	8.145
Triangle	12	14	28.805
	20	16	90.704
	8	16	38.585
Polygon	12	26	96.581
	20	29	246.799

Table 2.	Configuration	Ontimization	Performance
1 apre 2.	Conngulation	Optimization	I CITOI mance

Algorithm 1 Configuration optimization

**Input:** The vector of angles  $\vec{\Theta}$ ;

**Output:** The vector of mass M; The vector of geometry constrains Ğ.

- 1: // initilization
- 2:  $k \leftarrow 1$
- 3:  $\tilde{D}_{qb} \leftarrow \text{DBL}_{MAX}$
- 4: for each particle  $\gamma_i \ i \in [1, m]$  do
- Initialize particle's position  $\gamma_i = (M_i^0, G_i^0)$  randomly 5:
- Initialize particle's local best position  $\gamma_{li}^0 = \gamma_i^0$  randomly 6:
- $$\begin{split} & \Gamma_i^0 \leftarrow simulateShape(\gamma_i^0) \\ & \widetilde{D}_i^0 \leftarrow \widetilde{D}(T, \Gamma_i^0) \end{split}$$
  7:
- 8:
- 9: if  $\widetilde{D}_i^0 < \widetilde{D}_g$  then
- Update global best position  $\gamma_q \leftarrow \gamma_i^0$ 10:
- 11: end if
- Initialize particle's velocity  $V_i^0$  randomly 12:
- $\vec{D}_i^0 \leftarrow \vec{D}(T, \Gamma_i^0)$ 13:
- 14: end for
- 15: **for** each particle  $\gamma_i \ i \in [1, m]$  **do**
- 16:  $[\gamma_{bi}^{0}, \gamma_{wi}^{0}] \leftarrow selectionPrinciple(\vec{D^{0}})$ 17: end for
- 18: // iteration

while k < max-Iteration-Number or  $\widetilde{D}(T, \Gamma_{qb}) > \epsilon$  do 19:

- // Update velocity and location of particles 20
- 21:
- 22:
- 23:
- 24:
- for each particle  $\gamma_i \ i \in [1, m]$  do  $V_i^k \leftarrow V_i^{k-1} + rand()(\gamma_{li}^{k-1} \gamma_i^{k-1})$   $V_i^k \leftarrow V_i^k + rand()(\gamma_{g}^{k-1} \gamma_i^{k-1})$   $V_i^k \leftarrow V_i^k + rand()(\gamma_{bi}^{k-1} \gamma_i^{k-1})$   $V_i^k \leftarrow V_i^k + rand()(\gamma_{bi}^{k-1} \gamma_i^{k-1})$   $P_i^k \leftarrow V_i^{k-1} + V_i^k$ 25
- 26:
- 27: end for 28
- // update fitness variables 29
- **for** each particle  $\gamma_i \ i \in [1, m]$  **do** For each particle  $f_i \in [1,m]$   $\Gamma_i^k \leftarrow simulateShape(\gamma_i^k)$   $\vec{D}_i^k \leftarrow \vec{D}(T,\Gamma_i^k)$   $\vec{D}_i^k \leftarrow \vec{D}(T,\Gamma_i^k)$ end for 30:
- 31:
- 32: 33:
- 34:
- for each particle  $\gamma_i \ i \in [1, m]$  do if  $\widetilde{D}(T, \Gamma_i^k) < \widetilde{D}(T, \Gamma_{li}^{k-1})$  then 35:
- Update local best position  $\gamma_{li}^k \leftarrow \gamma_i^k$ 36
- end if 37:
- if  $\widetilde{D}(T, \Gamma_i^k) < \widetilde{D}(T, \Gamma_{qb})$  then 38
  - Update global best position  $\gamma_{qb} \leftarrow \gamma_i^k$
- end if 40

39:

- end for 41:
- **for** each particle  $\gamma_i$   $i \in [1, m]$  **do** 42:
- $[\gamma_{hi}^0, \gamma_{wi}^0] \leftarrow selectionPrinciple(\vec{D^k})$ 43:
- end for 44
- $k \leftarrow k + 1$ 45
- 46: end while