International Conference on Control, Automation and Systems 2010
Oct. 27-30, 2010 in KINTEX, Gyeonggi-do, Korea

# Behavioral performance of multi-robots driven by human drawing

Youngrae Jo[1] and Sungho Jo[2]

[1]Robot Program, KAIST, Daejeon, Korea
(Tel : +82-42-350-7840; E-mail: joyrae@kaist.ac.kr)
[2]Department of Computer Science, KAIST, Daejeon, Korea
(Tel : +82-42-350-3540; E-mail: shjo@cs.kaist.ac.kr)

**Abstract:** This work addresses the problem of behavioral performance of multi-robots corresponding to human drawing inputs in the sense of friendly human-robot interaction. We propose a drawing interface algorithm with multi-robots based on the centroidal Voronoi tessellation and the continuous-time Lloyd algorithms which have popularly been used for sensing and coverage control of multi-robots. Multi-robots can perform some meaningful behaviors through the real-time density functional update which reflects human drawings. Three drawing modes (distribution, following, and dancing modes) are implemented. Simulation tests verify the feasibility of the proposed algorithm.

**Keywords:** Multi-robots, Centroidal Voronoi tessellation, Density function, Human-Robot Interaction.

## 1. INTRODUCTION

The deployment of large groups of autonomous vehicles is rapidly becoming possible because of technological advances in networking and in miniaturization of electro-mechanical systems. In the near future, large numbers of robots will perform challenging tasks including search and recovery operations, manipulation in hazardous environments, exploration, surveillance, and environmental monitoring for pollution detection and estimation.

The underlying algorithmic principles to realize various multi-robot applications have extensively been investigated [1][2][3][7]. [1] explained the continuous Lloyd algorithm for coverage control. The coverage problem with heterogeneous robots was solved in [2]. Furthermore, it was proven that the same principles are still feasible for anisotropic sensor types [3].

This paper presents a new application of the multi-robot coverage problem, human drawing-based interface with multi-robots. As a friendly human-robot interaction method, especially, with multi-robots, drawing may be a good choice because of its easiness and familiarity. This paper suggests a way of interpreting the drawing with respect to the multi-robot coverage problem, and evaluates the feasibility of the proposed method through simulation tests.

The remainder of this paper is organized as follows. Section 2 reviews the locational optimization problem, the centroidal Voronoi tessellations and the continuous time Lloyd algorithms. In Section 3, we design density functions that drive the motions of multi-robots corresponding to drawings, and propose three drawing modes. Section 4 illustrates the empirical simulation results to verify the proposed approach, and section 5 concludes this work and summarizes the future works.

This work was supported by the Korea government(MKE) under Human Resources Development Program for Convergence Robot Specialists.

## 2. LOCATIONAL OPTIMIZATION

Let $Q$ be a convex polytope in $R^N$ including its interior, and $R_+$ be the set of nonnegative real numbers.

A distribution density function is defined to represent a measure of information or probability that an event takes place over $Q$ as a mapping $\rho : Q \to R$. Let $P = (p_1,...,p_n)$ be the locations of $n$ robots, each moving in the space $Q$. Because of noise and loss of resolution, the sensing performance at point $q$ taken from $i$th robot at position $p_i$ degrades as the distance $\parallel q - p_i \parallel$ is longer where $\parallel \cdot \parallel$ denotes the Euclidean distance function. The degradation can be described with a non-decreasing differentiable function $f : R_+ \to R_+$. Accordingly, $f(\parallel q - p_i \parallel)$ is a quantitative assessment of how poor the sensing performance is. A partition of $Q$ is a collection of n polytopes $W = W_1, ..., W_n$ with disjoint interiors whose union is $Q$.

We consider the task of solving the locational optimization problem by minimizing a cost function of

$$H(P, W) = \sum_{i=1}^{n} \int_{W_i} f(\parallel q - p_i \parallel)\rho(q)dq$$

under the assumption that $i$th sensor is responsible for measurements over its dominance region $W_i$. The cost function $H$ is minimized with respect to both the robot locations $P$ and the assignment of the partitioned dominance regions $W$. It is proven [8] that, with fixed robot locations, the optimal partition of $Q$ which is a convex polytope in $R^N$ including its interior is the Voronoi partition $V(P)$={$V_i, ..., V_n$} generated by the points $(p_i, ..., p_n)$ where

$$V_i = \{q \in Q \mid \parallel q - p_i \parallel \leq \parallel q - p_j \parallel, \forall j \neq i\}.$$

### 2.1 Centroidal Voronoi tessellation

An important concept to solve the locational optimization problem is the Voronoi tessellation. Given a set of points $P = \{p_1, ..., p_n\}$, often called sites, distributed over the bounded domain $Q$, with boundary $\partial Q$, the Voronoi region, or Voronoi cell, $V_i$, associated to the point $V_i$ is defined according to a given distance function $d$ as

$$V_i = \{q \in Q \mid d(q, p_i) \le d(q, p_j), \forall j \neq i\}.$$

The generalized Voronoi tessellation of the set $P$, $V(P)$, is the collection of such regions. The Voronoi boundary $\partial V_i$ is defined as

$$\partial V_i = \bigcup_{j=1}^{n} l_{ij} \bigcup \{\partial Q \bigcap V_i\},$$

where $l_{ij} = \{q \in Q \mid d(q, p_i) = d(q, p_j), j \neq i\}$.

Assuming that $W$ is determined by the Voronoi tessellation of the points in $P$, then $H(P, W) = H(P, V(P)) = H(P)$.

In this work, $f(\| q - p_i \|) = \| q - p_i \|^2$.

By recalling some basic quantities associated to a region $V \subset R^N$ and a density function $\rho$. the (generalized) mass, the centroid (or center of mass), and the polar moment of inertia are defined respectively to be

$$M_v = \int_V \rho(q) dq, C_V = \frac{1}{M_V} \int_V q\rho(q) dq,$$
$$J_{V,p} = \int_V \| q - p \|^2 \rho(q) dq.$$

[4] explains closed form expressions of the mass, the centroid, and the polar moment of inertia for uniform densities over $R^N$. See also [1] for their expressions in the $R^2$ setting.

Application of the parallel axis theorem leads to computational simplification

$$H_V(P) = H_{V,1} + H_{V,2}$$

where $H_{V,1} = \sum_{i=1}^{n} J_{V_i, C_{V_i}}$ and $H_{V,2} = \sum_{i=1}^{n} M_{V_i} \| p_i - C_{V_i} \|^2$. Then, $\frac{\partial H_{V,1}}{\partial p_i} = 0$, $\frac{\partial H_{V,2}}{\partial p_i} = 2M_{V_i}(p_i - C_{V_i})$ and therefore,

$$\frac{\partial H_V}{\partial p_i}(P) = 2M_{V_i}(p_i - C_{V_i}).$$

Local minimum points for the location optimization problem are computed by setting the partial derivatives to zero. Hence,

$$C_{V_i} = \arg\min_{p_i} H_V(P),$$
$$H_{V,1} = \min_{(p_1,\ldots,p_n)} H_V(P).$$

A local optimal point of is the centroid of the Voronoi cell and the generator of the cell as well. Accordingly, the cell partitions and optimal points employ the centroidal Voronoi tessellation. See [5] for details.

### 2.2 Continuou-time LloydAlgorithm

A typical discrete-time method to compute the centeroidal Voronoi Tessellation is the Lloyds algorithm [7]. The method executes three steps over iterations,

i. Computation of the Voronoi regions;
ii. Computation of the centroids;
iii. Point relocation to the corresponding centroid.

[1] proposed a gradient descent flow-based algorithm to evolve the partitions and the locations in continuous time. In [1], a continuous-time version of this approach is proposed considering a first order dynamic motion in the form of $\dot{p_i} = u_i$. By designing a controller to be

$$u_i = -k(p_i - C_{V_i})$$

where $k$ is a positive gain and where $C_{V_i}$ is computed according to continuously updated partition $V(P) = \{V_1, ..., V_n\}$, locational stabilization to local minima is guaranteed. The control algorithm is a gradient descent flow, since

$$\frac{\partial H}{\partial p_i} = -2k \sum_{i=1}^{n} M_{V_i} \| p_i - C_{V_i} \|^2 \le 0.$$

## 3. HUMAN DRAWING INPUT

This work proposes to make use of the multi-robots locational optimization problem described in previous section to implement an interface method with multi-robots. A scenario under consideration is as follows. A human draws figures, and multi-robots behave correspondingly to the figures in real-time. The robot motion can be interpreted visually meaningful.

$q = (x, y) \in Q \subset R^2$ denotes a location in a planar environment. Consider a uniform distribution density function, for example, $\rho(q) = 1$. Using the density function, the locational optimization solution deploys robots uniformly over the space.

Our idea is to present input commands using a real-time change of a density function. In a canvas region on the PC, we draw lines or objects using a mouse or a similar tool. The drawing generates a corresponding density function. The density function is updated continuously in real-time as further drawing is implemented. Then, multi-robot operations are performed through the centroidal Voronoi tessellation and the continuous-time Lloyd algorithms using the density function. We declare three types of density functions. The density functions specify different drawing modes respectively: distribution mode, following mode, and dancing mode.

During the distribution model, robots are distributed corresponding to the most recently updated density function. Sometimes, the robot distribution depicts the overall drawing. In the following mode, the robots tend to converge the most recent part of drawing. Therefore, apparently robots seem to chase a drawing tool. Lastly, the dancing mode pursues more dynamic robot motions.

First, to implement the distribution mode, a density function is declared. Let $q_m(t) = (x_m(t), y_m(t))$ indicate a drawing point in space $Q$ where $t$ represents a sampling time $(t = 0, 1, 2, ..., T)$ and let $T$ be the number of drawing points until now. Considering the Gaussian density function,

$$\rho_t(q) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x - x_m(t))^2 + (y - y_m(t))^2}{2\sigma^2}},$$

where $\sigma$ specifies the width of the Gaussian function, we define a density function of the drawing as follows.

$$\rho(q) = \max_{t=0,1,\ldots,T}(\rho_t(q))$$

In the following mode, the effectiveness of drawing points in the past is faded out, and recent drawing points are relatively more influential in the density function. The characteristics can be realized as follows.

$$\rho(q) = \omega\rho_{T-1}(q) + \rho_T(q)$$

where $\omega$ is a decaying factor whose value is greater than zero and less than one.

The dancing mode takes into account the drawing speed in order for robot motions to be more variant and diversified, therefore, to be more likely to be dancing. The density function formulation in this mode is equal to that in the following mode, but quick or slow drawing motion is employed to set the variance term to be, instead of a constant, as follows.

$$\sigma(T) = \sigma_0\sqrt{(x_m(T) - x_m(T-1))^2 + (y_m(T) - y_m(T-1))^2}$$

where $\sigma_0$ is a constant.

When drawing is fast, the $\sigma$ value tends to be large, and robots tend to spread out relatively. Slow drawing drives a small $\sigma$ value, therefore, robots tend to gather together.

## 4. SIMUALATION TESTS

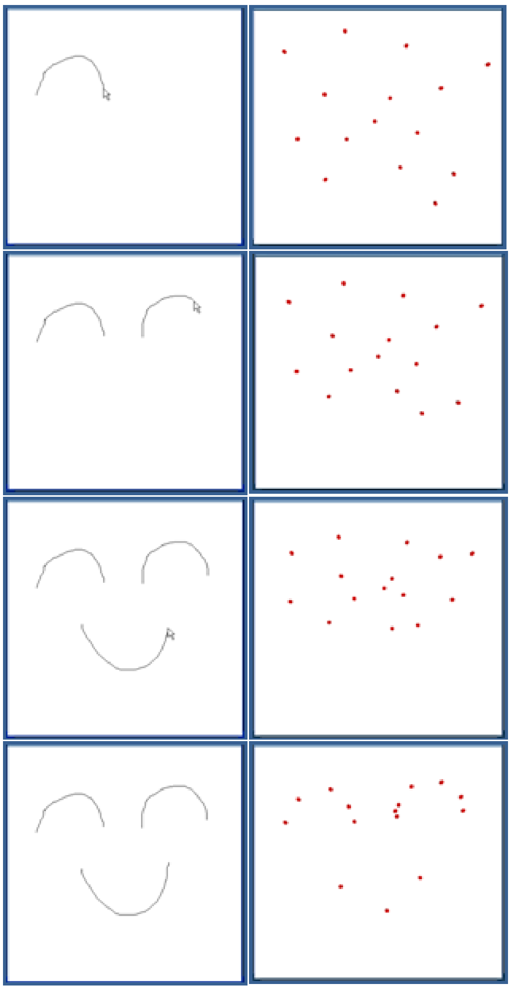

Fig. 1 A simulated multi-robot performance in the distribution mode $(n = 15, \sigma = 3)$. Snapshots in the left column illustrate human drawing and snapshots in the right column show corresponding robot performance in real-time.

We developed a drawing interface software integrated with a robot simulator, Simbad 3D [9]. A human draws in a drawing window and a density function is extracted accordingly from the drawing and the locational optimization algorithm is applied based on the density function. Then, the interface software simulates multi-robot performances computationally.

Fig. 1 illustrates a multi-robot performance in the distribution model. Each robot location is expressed by a dot. The robots are randomly located initially, but eventually converge to a certain placement corresponding to the drawing input.

Fig. 2 shows a simulation in the following mode. Robots tend to chase the recent part of drawing. In the dancing mode, the drawing speed affects the robot behaviors. In Fig. 3, a simulation test demonstrates that robots are spread or gathered depending on the drawing speed.

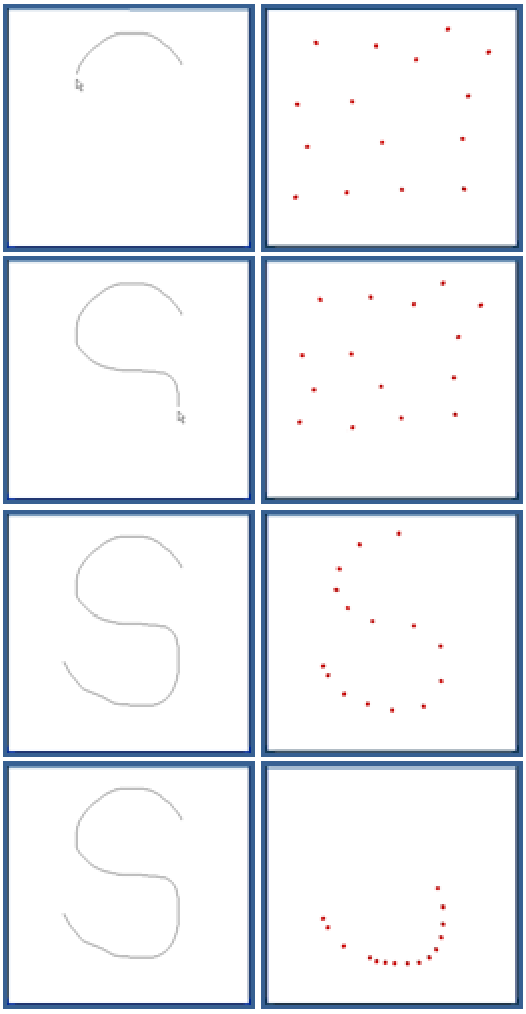

Fig. 2 A simulated multi-robot performance in the following mode $(n = 15, \sigma = 3, \omega = 0.7)$. Snapshots in the left column illustrate human drawing and snapshots in the right column show corresponding robot performance in real-time.

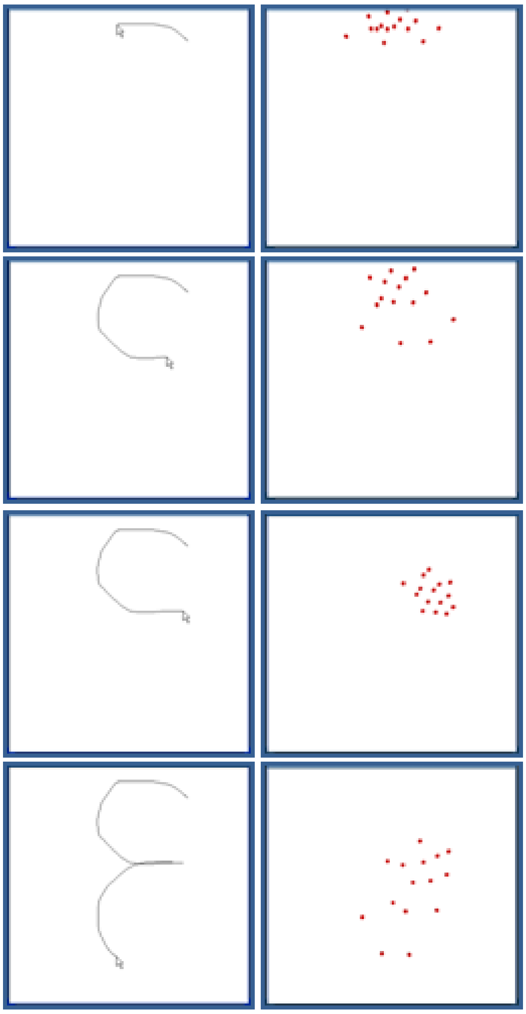

Fig. 3 A simulated multi-robot performance in the dancing mode $(n = 15, \omega = 0.7, \sigma_0 = 5)$.Snapshots in the left column illustrate human drawing and snapshots in the right column show corresponding robot performance in real-time.

## 5. CONCLUSION

This work presented a friendly interface method with multi-robots using drawings. Multi-robots move responding to human drawing inputs. The drawing is expressed by a corresponding density function, which is applied to the locational optimization problem. Three drawing modes are proposed to demonstrate different robot performances. In the future work, the proposed approach will be used to conduct experiments with real robot implementation.

## REFERENCES


[1] J. Cortes, S. Martinez, T. Karatas and F. Bullo, "Coverage Control for Mobile Sensing Networks," *IEEE Transactions on Robotics and Automation*, Vol. 20, No. 2, pp. 243-255, 2004.

[2] L. C. A. Pimenta, V. Kumar, R. C. Mesquita, and G. A. S. Pereira, "Sensing and Coverage for a Network of Heterogeneous Robots," *In Proc IEEE Conference on Decision and Control*, Cancun, Mexico, 2008.

[3] A. Gusrialdi, S.Hirche, T. Hatanaka and M. Fujita, "Voronoi based coverage control with anisotropic sensors," *American Control Conference*, pp. 736-741, 2008.

[4] C. Cattani and A. Paoluzzi, "Boundary integration over linear polyhedral", *Computer-Aided Design*, Vol. 22, No. 2, pp. 130-135, 1990.

[5] Q. Du, V. Faber, and M. Gunzburger, "Centroidal Voronoi Tessellations : applications and algorithms", *SIAM Review*, Vol. 41, No. 4, pp.637-676, 1999.

[6] M. Schwager, J. J. Slotine, and D. Rus, "Unifying geomertric, probabilistic, and potential field approaches to multi-robot coverage control", *In Proc ISRR*, 2009.

[7] S. P. Lloyd, "Least Squares Quantization in PCM", *IEEE Transactions on Information Theory*, Vol. 28, pp. 129-137, 1982.

[8] A. Okabe, B. Boots, K. Sugihara and S.N. Chiu, *Spatial Tessellations: concepts and applications of voronoi diagrams*, Wiley, New York, 1992.

[9] Http://simbad.sourceforge.net/.