Cluster-Structured Particle Swarm Optimization with Interaction and Adaptation

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Keywords: Meta-heuristics, Particle Swarm Optimization, Cluster-Structure, Interaction, Adaptive Algorithm

1. Introduction
Particle Swarm Optimization (PSO) is one of the most powerful methods available for solving unconstrained global optimization problems. This paper proposes an adaptive PSO with cluster structure, interaction, and adaptation in order to achieve an appropriate balance between diversification and intensification during its search process. While the population of adaptive PSO is divided into two or more than subgroups (clusters) with adaptation in the proposed PSO, an appropriate interaction among clusters is added. Numerical experiments using some typical benchmark problems validate the search performance of the proposed PSO.

2. Cluster-Structured PSO
As mentioned above, the cluster-structured PSO with interaction and adaptation is constructed by not only dividing the adaptive PSO into two or more than clusters but also providing appropriate interaction and adaptation among clusters in order to obtain an appropriate balance between diversification and intensification.

The algorithm of Cluster-Structured PSO is as follows:

[Cluster-Structured PSO]

Step 0: [Preparation]
Set the number of parameters $2 \leq N_C$, $m \in N^1$, $c_3=0.3$, $g_{di} = 0$, $a_{d} = 0$, $d = 1, 2, \cdots, N_C$; $i = 1, 2, \cdots, m$; maximum iteration number $T_{\text{max}}$ and $k = 1$.

Step 1: [Initialization]
$x_{d1}, v_{d1} \in R^c$, are set at random. Parameters $w_{d1}, c_{1d}, c_{2d}$ are determined using random number in ranges to $0.75 \leq w_d \leq 0.85$, $0 \leq c_{1d} \leq 3$, $0 \leq c_{2d} \leq (3 - c_{1d})$ are set.

Step 2: [Updating $v_{d1}$ and $x_{d1}$]
\[
\begin{align*}
    v^{k+1}_{dij} & = v_{dij}^k + c_{1d} \cdot \text{rand}_{dij} \cdot (p_{\text{best}_{dij}}^k - x_{dij}^k) + c_{2d} \cdot \text{rand}_{dij} \cdot (g_{\text{best}_{dij}}^k - x_{dij}^k) \\
    x_{dij}^{k+1} & = x_{dij}^k + v_{dij}^{k+1}
\end{align*}
\]
d = 1, 2, \cdots, N_C; $i = 1, 2, \cdots, m$; $j = 1, 2, \cdots, n$.

Step 3: [Updating $p_{\text{best}_{dij}}, g_{\text{best}_{dij}}$, and $a_{\text{best}_{d1j}}$]
\[
\begin{align*}
    I_1 & = \{ i | f(x_{dij}^{k+1}) < f(p_{\text{best}_{dij}}^k), d = 1, 2, \cdots, N_C, \\
    i & = 1, 2, \cdots, m \} \\
    p_{\text{best}_{dij}}^{k+1} & = x_{dij}^{k+1}, \ di \in I_1, \\
    p_{\text{best}_{dij}}^k & = p_{\text{best}_{dij}}^{k+1}, \ di \notin I_1
\end{align*}
\]

Step 4: [Determining Parameter $\alpha$]
If $f(p_{\text{best}_{dij}}^{k+1}) > f(g_{\text{best}_{dij}}^k)$, then $\alpha_{d}^k = 0$,
d = 1, 2, \cdots, N_C; $i = 1, 2, \cdots, m$.
Otherwise,
\[
\begin{align*}
    g_{d\alpha} & = g_{d\alpha} + 1 \\
    I_2 & = \{ i | g_{d\alpha} < d_{\alpha}, \ di \notin d_{\alpha} \} \\
    \beta_{d}^k & = 1/T_{\text{max}}, \ di \in I_2
\end{align*}
\]

Step 5: [Determining Parameter $\beta$]
If $f(p_{\text{best}_{dij}}^{k+1}) > f(g_{\text{best}_{dij}}^k)$, then $\beta_{d}^k = 0$,
d = 1, 2, \cdots, N_C.
Otherwise, $a_{d} = a_{d} + 1$,
\[
I_3 = \{ i | a_{d} < a_{d}, \ di \notin d_{\alpha} \} \\
\beta_{d}^k = 0, \ di \notin I_3, \beta_{d}^k = 1/T_{\text{max}}, \ di \in I_3
\]

Step 6: [Updating Parameters $w_{d1}$ and $c_{2d}$]
\[
\begin{align*}
    c_{1d}^{k+1} & = c_{1d}^k + \alpha_{d} \cdot (c_{1d} - c_{1d}^k) \\
    c_{2d}^{k+1} & = c_{2d}^k + \alpha_{d} \cdot (c_{2d} - c_{2d}^k) \\
    w_{d1}^{k+1} & = w_{d1}^k + \beta_{d} \cdot (w_{d1}^{k+1} - w_{d1}^k)
\end{align*}
\]
d = 1, 2, \cdots, N_C; $i = 1, 2, \cdots, m$.

Step 7: [Checking Termination Criterion]
If $k = T_{\text{max}}$, then terminate. Otherwise, set $k = k + 1$, and return to Step 2.

3. Numerical Experiment
We compare performance of the proposed PSO, Constriction Method(CM), Linearly Decreasing Inertia Weight Method(LDIWM), Adaptive PSO(APSO) and Pursuit-Escape PSO(PEPSO). The simulation results are shown in Table 1. The performance of the proposed PSO is more powerful than that of the other methods.

Table 1. Simulations to compare performance of the proposed method with that of other methods

<table>
<thead>
<tr>
<th>Problem</th>
<th>CM</th>
<th>LDIWM</th>
<th>APSO</th>
<th>PEPSO</th>
<th>Proposed PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rosenbrock</td>
<td>Best: 399.136</td>
<td>370.777</td>
<td>188.115</td>
<td>297.645</td>
<td>9560*</td>
</tr>
<tr>
<td>1000 Dim.</td>
<td>Mean</td>
<td>406.70</td>
<td>406.825</td>
<td>271.17</td>
<td>375.324</td>
</tr>
<tr>
<td>Rastrigin</td>
<td>Best: 136.30</td>
<td>170.94</td>
<td>6455</td>
<td>9905</td>
<td>5473*</td>
</tr>
<tr>
<td>1000 Dim.</td>
<td>Mean</td>
<td>157.75</td>
<td>177.71</td>
<td>7272</td>
<td>10300</td>
</tr>
</tbody>
</table>

Std Dev: 99.38 | 996.4 | 6785 | 36095 | 4807 | 591
Generation of the Motion of the Robot Using Simultaneous Parallel GA by Single Population

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Keywords : robot motion, genetic algorithm, multi-problems, single population

1. Introduction
Recently, Humanoid robot has been used in various fields. Because a robot has many degrees of freedom, its motion design is difficult. The conventional method of a motion design of robot, such as motion capture method, restricts human’s motion, place, object, etc. Therefore, it is necessary to simplify the method design of humanoid robot by reducing these limitations. Here, we propose the method of motion design that reduces these limitations and avoids complex calculation. In this paper, we propose the method of motion design by dealing with the alteration of the model captured by single camera and generate imitation motion of robot using optimization of genetic algorithm (GA). We think that this method could also work with 3-dimensional (3D) motion of robot considering the operation limit of human joints and robot’s.

2. Proposed Method
The method generates the imitation motion of the robot from the model taken by motion pictures of front view human motion. Since it is difficult to imitate the model of dynamic motion pictures, we divided and extracted the motion pictures into several poses pictures. These poses pictures are then compared with the image of front view robot poses generated by 3D simulator. The proposed method generates imitation motions of robot using optimization of GA.

Normally, we generate the imitation motions of robot from each picture of pose model sequentially. We named this method by Sequential Method. By using this method, there will be repetitive task in the process of generating each pose, since the pictures of pose model extracted from sequence action are nearly similar each other. We propose the method of generating several poses in parallel with one GA at the same time. We named this method by Simultaneous Parallel Method.

3. Experiment of Results
We evaluated the proposed method through experiment using computer simulation. Fig. 1 shows the pose images that divided and extracted from a model motion pictures. Fig. 2 shows the experiment results for motion 1 in Fig. 1. Fig. 3 shows the experiment results for motion 2 in fig. 1. It can be confirmed that the poses of robots in Fig. 2 and Fig. 3 resemble the poses of model human in Fig. 1. The processing time of Simultaneous Parallel Method is less than half of the processing time of Sequential Method to generate the imitation motion of robot.

4. Conclusion
We proposed the method for generating the imitation motion of robot using optimization of GA and motion pictures that took from the front view of human motion. This method has decreased the limitation of human motion and exercising place. The method could also work with 3D motion of robot considering of the operation limit of human joints and robot’s, even by using only single camera. We confirmed that Simultaneous Parallel Method took less time and better result compared with Sequential Method.

As the future problem, it is necessary to add processing to make the pose image of human to be similar with the shape of robot, since errors occurred for the result of difference between the shape of human and robot. It is also necessary to add processing to generate dynamic motion of the robot.

Fig. 1. Model images (From left to right No.1~)
(a) Sequential method
(b) Simultaneous parallel method

Fig. 2. Results for motion 1
(a) Sequential method
(b) Simultaneous parallel method

Fig. 3. Results for motion 2
Simultaneous parallel method
**Ensemble Image Classification Using Genetic Image Network as Weak Classifiers**

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**Keywords:** image classification, evolutionary computation, AdaBoost, genetic programming, image processing

Automatic construction method for image classification algorithms has been required, but it is very difficult to construct an algorithm suitable for all image classification problems. Therefore, a method is required to construct an image classification algorithm that would automatically adjust to the target problem is needed. Genetic Image Network for Image Classification (GIN-IC) is one of the methods that construct image classification algorithms automatically, and its effectiveness has already been proven. GIN-IC automatically constructs the adequate classification algorithm using evolutionary computation. The process of GIN-IC is, first, to transform original images to easier-to-classify images using image transformation nodes, and next, to select adequate image features using feature extraction nodes. The greatest advantage of GIN-IC is its image transformation component, which influences image feature selection. However, learning failure or over fitting of the training images sometimes occurs in the constructed algorithms because of GIN-IC’s simple output to decide the classification.

In this paper, we extend GIN-IC by adding the AdaBoost algorithm. In our method, a set of output nodes in GIN-IC is treated as a weak classifier. Fig. 1 shows an example of a structure in our proposed method for binary classification. Weak classifiers are evolved in sequence until each weak classifier achieves a specified error rate. In this process, the construction of the previous weak classifiers is fixed and can be reused in the subsequent weak classifiers. The effective process of other weak classifiers can be reused. Moreover, reuse is expected to reduce the time required for learning by avoiding recalculation at each operational node. The final hypothesis is a weighted vote of the hypothesis of all weak classifiers.

We evaluate our proposed method by applying it to three image classification problems, texture, pedestrian and generic object images. In the experiments, we prepare simple and well-known operations as each operation node. We compare our proposed method with GIN-IC in discrimination rate for training and test images and time required for learning. The results are the average (Ave) and the standard deviation (SD) over 10 different runs.

Discrimination rates for the training and test images of three experiments are shown in Table 1. Our proposed method classified all training images completely in all runs and tends to prevent over fitting as compared to single GIN-IC in three experiments. We confirmed that GIN-IC and AdaBoost go well together. Our proposed method also obtained higher classification accuracy for test images as compared to GIN-IC totally. Moreover, our proposed method took lesser time than single GIN-IC, for learning. We attribute this superiority to using GIN-IC as weak classifiers.

We have shown the effectiveness of our proposed method. Since we use GIN-IC as weak classifiers, our proposed method can generate and select adequate image features by a combination of nodes. Although we only used simple image processing filters and image features as nodes in these experiments, we think that the performance is improved by adding more complex and effective processes.

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**Fig. 1.** Example of a structure in proposed method for binary classification.

| Table 1. Discrimination rate for the training and test images in three experiments. |
|------------------|------------------|------------------|------------------|------------------|
|                  | Training set     | Test set         |                  |
| Problem          | GIN-IC           | Proposal         | GIN-IC           | Proposal         |
|                  | Ave              | Ave ± SD         | Ave              | Ave ± SD         |
| Texture          | 98.0%            | 100.0%           | 82.8 ± 8.2%     | 94.7 ± 1.5%     |
| Pedestrian       | 90.1%            | 100.0%           | 80.5 ± 6.1%     | 87.2 ± 3.7%     |
| Object           | 92.4%            | 100.0%           | 59.1 ± 6.3%     | 76.3 ± 3.5%     |
A Growing Complex Network Design Method

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Keywords: Complex Network, Multi-objective Optimization, Growing Network, Network Design, Multi-objective Genetic Algorithm

A complex network design method that finds a desired network structure can become one of strong tools in large-scale system designs. Conventional complex network design methods only tackle static networks, that is, they do not consider the growth of a target network.

In this study, we propose a new growing complex network design method. First, let us consider evaluation functions which quantitatively express characteristics of desired structures using feature quantities. Then, we formulate a growing complex network design problem as a multi-objective optimization problem in order to determine connection targets of a new node using the evaluation functions. The formulation is given by

$$\min_{X'} f(X') \quad \text{subject to} \quad i = 1, \ldots, N, j = 1, \ldots, N$$

where $X$ is a network which is formed by adding a node to a network $X'$ and $f$ is the evaluation function vector. Solving the problem, we grow the network. Then, we obtain a desired network.

We try to generate networks which have desired clustering coefficient and average path concurrently. We use the genetic algorithm with MGG in which the original problem is transformed into a weighted aggregation problem, SPEA2, and NSGA-II as the multi-objective optimization method. The results are shown in Fig. 1 and Fig. 2. The results show the proposed method is effective as a growing complex network design method.

![Fig. 1. Transition of average path w.r.t. growth of the network](image1)

![Fig. 2. Transition of clustering coefficient w.r.t. growth of the network](image2)
Switching Reinforcement Learning for Continuous Action Space

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Keywords: reinforcement learning, action space design, state space design, entropy, simulation

Reinforcement Learning (RL) attracts much attention as a key technique of realizing computational intelligence such as adaptive and autonomous decentralized systems. In general, however, it is not easy to put RL into practical use. This difficulty includes a problem of designing a suitable action space of an agent, i.e., satisfying two requirements in trade-off: (i) to keep the characteristics (or structure) of an original search space as much as possible in order to seek strategies that lie close to the optimal, and (ii) to reduce the search space as much as possible in order to expedite the learning process.

In order to design a suitable action space adaptively, we propose switching RL model to mimic a process of an infant’s motor development in which gross motor skills develop before fine motor skills, as shown in Fig. 1. Here, the controller based on a learning device for discrete actions (hereafter called “DA controller”) acquires gross motor skills, and the other controller based on a learning device for continuous actions (hereafter called “CA controller”) acquires fine motor skills.

Then, a switching method is constructed by introducing and referring to the “entropy”, which is defined on action selection probability distributions using Boltzmann selection in a state and the number of learning opportunities in the state. The switching method treats this entropy $H(s)$ as an index of sufficiency for the number of learning opportunities in $s$. The controller is switched to the AC controller, if the following formula is satisfied: $H(s) < \theta_L$. In parallel, the controller is also switched to the CA controller, if the following simple formula regarding the number of learning opportunities in $s$, $L(s)$, is satisfied: $L(s) > \theta_L$, where $\theta_L$ is set at a sufficiently big number. This is used because the entropy can not be small after the controller learned a sufficient number of times, if the state space is designed too coarse-grained. In this paper, Q-learning and Actor-Critic are applied to the DA controller and the CA controller respectively.

Further, through computational experiments by using robot navigation problems with one and two-dimensional continuous action space, the proposed method is compared with an Actor-Critic method and three Q-learning methods where the number of actions is designed and a method based on Actor-Q architecture. The number of steps required to accomplish these task have been observed are described in Fig. 2, 3. As the result, the validity of the proposed method has been confirmed.

Fig. 1. Proposed switching reinforcement learning model

Fig. 2. Required steps for the task (1)

Fig. 3. Required steps for the task (2)
Evolutionary Structure Optimization of Hierarchical Neural Network for Image Recognition

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Keywords: Neural Network, Genetic Algorithm, Face Recognition, Texture Classification

The purpose of this paper is to optimize the structure of hierarchical neural network (NN). In our proposed method, the structure optimization is considered as combinatorial optimization problem, and unnecessary connections in trained NN are eliminated by using genetic algorithm (GA). We focus on the NN which specialized for image recognition problems. In order to validate the usefulness of the proposed method, face recognition and texture classification examples are used. From the experimental results, it was shown that compact neural network was generated, keeping generalization performance by proposed method.

We show the flow of the proposed method in Fig.1. First of all, walsh-hadamard transform is applied to images to extract features. Secondly, NN is trained with extracted features based on back-propagation (BP) algorithm. After NN training, unnecessary connections are eliminated from trained NN by utilizing GA. Finally, NN is retrained with BP algorithm to recover the degradation caused by connection elimination.

To verify the usefulness of the proposed method, we construct two kinds of NN for face recognition and texture classification. Constructed NN is evaluated in terms of its square error and reduction rate of the number of connections. Here, we show the results of face recognition examples. Table 1 shows square error of constructed NN which has different number of hidden units. Where “BP only” and “BP+GA” indicate the networks generated by BP algorithm only, and BP algorithm and GA (not include retraining), respectively.

Square error was calculated with test image which is different from training image to evaluate generalization performance. The results indicate that proposed method was better than BP+GA and slightly worse compared with BP only. Then, we show the reduction rate in Fig.2. The reduction rate was calculated from Eq.(1).

$$\text{Reduction rate} = \frac{N_{\text{before}} - N_{\text{after}}}{N_{\text{before}}} \times 100 \%$$ (1)

Where $N_{\text{before}}$ and $N_{\text{after}}$ denote the number of connections before and after connection elimination, respectively. In Fig.2, about more than 60% of connections were eliminated from NN. On the other hand, the reduction rate declined as the number of hidden units increased, although a lot of hidden units generate similar type hidden units which should be eliminated. From the experimental results, we conclude that compact NN was generated, keeping generalization performance by proposed method.

Table 1. Square error on face recognition.

<table>
<thead>
<tr>
<th></th>
<th>8</th>
<th>16</th>
<th>32</th>
<th>64</th>
<th>128</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP only</td>
<td>0.035</td>
<td>0.024</td>
<td>0.029</td>
<td>0.029</td>
<td>0.026</td>
</tr>
<tr>
<td>BP+GA</td>
<td>0.731</td>
<td>0.500</td>
<td>0.416</td>
<td>0.384</td>
<td>0.317</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.059</td>
<td>0.081</td>
<td>0.049</td>
<td>0.039</td>
<td>0.052</td>
</tr>
</tbody>
</table>

Fig. 1. Flow of the proposed method.

Fig. 2. Reduction rate of the connection on face recognition.
A Constrained Global Optimization Method
Based on Multi-Objective Particle Swarm Optimization

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Keywords: constrained optimization, particle swarm optimization (PSO), multi-objective optimization, multi-objective particle swarm optimization (MOPSO)

1. Introduction
This paper proposes a constrained global optimization method based on Multi-Objective Particle Swarm Optimization (MOPSO). A constrained optimization problem is transformed into another bi-objective problem which minimizes both the original objective function and the total amount of constraint violations. Then, the global optimum of the former problem is obtained as the Pareto optimal solution of the latter one having no constraint violation. In order to find the particular Pareto optimal solution, the proposed method introduces additional operations to MOPSO. Numerical examples verify the effectiveness, efficiency and wide applicability of the proposed method.

2. Bi-Objective Problem Formulation
Consider to solve a general constrained problem:

$$\min_{x \in \mathcal{D}} f(x) \quad \text{subject to} \quad g_l(x) \leq 0, \quad l = 1, \ldots, L; \quad h_m(x) = 0, \quad m = 1, \ldots, M.$$ \quad (1a)

where $x \in \mathcal{R}^N$, $\mathcal{D} \subseteq \mathcal{R}^N$ is a connected set, and $f, g_l, h_m$, $m = 1, \ldots, M$ all map $\mathcal{D}$ to $\mathcal{R}$. For (1), the total amount of constraint violations can be defined by:

$$\mu(x) = \sum_{l=1}^{L} \max\{0, g_l(x)\} + \sum_{m=1}^{M} |h_m(x)|.$$ \quad (2)

With (2), the constrained problem (1) can be transformed into a bi-objective problem:

$$\begin{align*}
\min_{x \in \mathcal{D}} & \quad f(x) \quad \text{(3a)} \\
\min_{x \in \mathcal{D}} & \quad \mu(x) \quad \text{(3b)}
\end{align*}$$

It is obvious that the global optimum of (1) is equivalent to the Pareto optimal solution of (3) which vanishes the constraint violations. Fig. 1 depicts the attainable set and the Pareto front of (3). ‘X’, ‘Y’, ‘Z’, ... are feasible points of (1), and among them the Pareto optimal point ‘X’ corresponds to the global optimum of (1).

3. Proposed Method
The bi-objective problem (3) is solved by MOPSO. MOPSO generally searches for all Pareto optimal solutions, but to solve (1) one only needs to find the particular one. The proposed method adds the operations such as:

(a) restricting the number of Pareto optimal solutions obtained at each iteration of MOPSO,

(b) choosing the most promising Pareto optimal solution as the global best solution so as to exclude other solutions dominated by it,

(c) encouraging to add Pareto optimal solutions if the number of them is too small, to MOPSO. While (a) converges particles of MOPSO to feasible sets of (1), (c) recovers the diversity in the motion of particles. (b) helps to decrease both the objective function ($f$) and the constraint violations ($\mu$) values of particles.

4. Evaluation of the Proposed Method by Numerical Experiments
A series of problems, which have a common relatively simple objective function but which have different types of constraints each, were solved by the proposed method. With successful results, it was proved to be effective, efficient and widely applicable. Furthermore, some famous engineering design problems such as tension/compression string design (TC), welded beam (WB), and pressure vessel (PV), were also solved. Table 1 lists the best solution by the proposed method. For all problems, the proposed method could find no worse solutions than the previously known best ones with less function evaluations.

**Table 1.** Results for engineering design problems.

<table>
<thead>
<tr>
<th>prob.</th>
<th>best solution by the proposed method</th>
<th>$f$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TC</td>
<td>0.051689, 0.356728, 11.288372 etc.</td>
<td>0.0126652</td>
</tr>
<tr>
<td>WB</td>
<td>(0.244369, 1.276589, 8.291472, 0.244369)</td>
<td>1.573369</td>
</tr>
<tr>
<td>PV</td>
<td>(0.8125, 0.4375, 42.0981456, 176.639956)</td>
<td>6059.7143</td>
</tr>
</tbody>
</table>
The Autonomous Mobile Robot Controller Developed by RBF Network and Genetic Algorithm

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Keywords: integrated optimization system, autonomous mobile robot, RBF network, genetic algorithm

In this paper, we perform experiments where autonomous mobile robot controllers are developed by the integrative optimization system. Fig. 1 shows a wheel type mobile robot and the environment of experiments which are used in this paper.

Autonomous mobile robot controllers are developed using meta-heuristics, if the behavior of robot is able to be evaluated. However, in an actual environment, it is difficult to develop the robot controller using meta-heuristics because meta-heuristics requires a large number of function evaluations. And large numbers of function evaluations have problems which are to increase experimental time and the maintenance cost. The integrative optimization system is a method to improve these problems.

A general integrative optimization system constructs an approximate response surface by the radial basis function network and optimizes to the approximate response surface by the optimization method. The optimization method applied is Genetic Algorithms (GA) in this paper.

We perform experiments where the robot controllers are developed by the integrative optimization system in a simulator and actual environment. Through experiments, the proposed method where the robot controllers are developed by the integrative optimization system is compared to a conventional method by only GA.

The results of experiments in actual environment are shown in Fig. 2 (the conventional method) and Fig. 3 (the proposed method), and are given in Table 1. The results of experiments show that the proposed method is able to develop controllers by a small number of function evaluations, and therefore it is an effective method to develop the autonomous mobile robot controller.

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Table 1. Convergence rate, and average of convergence generation and convergence iteration.

<table>
<thead>
<tr>
<th></th>
<th>Conventional method</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convergence rate [%]</td>
<td>40.0</td>
<td>70.0</td>
</tr>
<tr>
<td>Average of convergence generation / iteration</td>
<td>18.3</td>
<td>12.6</td>
</tr>
</tbody>
</table>

---

Fig. 1. Wheel type mobile robot and environment of experiments.

Fig. 2. History of fitness (conventional method).

Fig. 3. History of fitness (proposed method).
Building of Reusable Reverse Logistics Model and its Optimization Considering the Decision of Backorder or Next Arrival of Goods

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Keywords : Reusable Recovery, Reverse Logistics, Backorder or Next arrival of Goods

For achievement of the resources recycling society and the low carbon society, the reverse logistics, which targets the flow from production recovery to reproduction of end of life products, receives attention in the logistics field. However, the reverse logistics is different from the traditional forward logistics where new material or part are produced and sold to customer. In the reverse logistics, it is not only hard to predict the appearing time or amount of arrivals by the used periods or condition of the recovered products, but also the recovery routes are complex as there are lot of recovery centers. Moreover, even though the recovery products are environment-friendly, its market is not large yet because of the stereotype of customers who regard the recovery product as used goods. And the reverse logistics costs more than the traditional forward logistics to construct and operate the system.

Therefore, for the optimization of the reverse logistics with uncertainty of amount or occurrence time of the recovery product, the building a model is necessary considering not only transportation cost but also the date and the processing of decision whether waiting for arrival of end-of-life product with unclear amount to the returning center or backordering necessary parts for manufacturing.

This paper builds a reusable reverse logistics model considering the decision of backordering or waiting for the next arrival of goods on the base of the reusable recovery. And, the optimization method of the reusable recovery to minimize the transportation cost and the volume of the backorder or the next arrival of goods occurred by the just in time delivery of the final delivery stage between the manufacturer and the processing center is described. In addition, this method can be applied also to the remanufacturing recovery and the recycling recovery.

Figure 1 describes the model combined decision factors of backordering or waiting for the next arrival of goods based on the total inventory of the manufacturer in case of end-of-life product ($x_{ai}(t)$) gathering goods to the processing center through the returning center is less than the amount of demand ($d_i$).

In this paper, the priority-based genetic representation and the fuzzy logic controller that improve search ability of GA by adjusting parameter appropriately in each generation and making situation by optimum solution search are used as the optimization methods of the reusable reverse logistics. Through the optimization algorithms using the priority-based genetic algorithm and the hybrid genetic algorithm, the sub-optimal delivery routes are determined.

To evaluate the effectiveness of the proposed model, the bottle reusable recovery case with a distilling and sale company in Busan in Korea was simulated. The empty bottles collected from the retailers are delivered to the manufacturing plant through the three kind of recovery center (shopping center, farming store, and recycle dealer), and these are reused after processing process. The empty bottles to be collected are Soju bottles, and they are collected once a day. And, the recovery center is 188 minimum administrative areas in 6233 retailers (supermarket) in the city. It set to 20 of population size, 0.7 of initial WMX crossover rate, 0.3 of initial mutation rate, and 5000 of maximum generation as a simulation condition of the genetic algorithm. As the result, the hybrid genetic algorithm is better than the priority-based genetic algorithm.

Figure 2 shows the sub-optimal delivery routes and the selected situation of the recovery center. In this sub-optimal delivery routes, the five recovery centers (dotted circle in Figure 2) are removed because of these high cost.
Extended Summary

Statistical Stability Analysis for Particle Swarm Optimization Dynamics with Random Coefficients

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Keywords: meta-heuristics, Particle Swarm Optimization, stability analysis

1. Introduction

Particle Swarm Optimization (PSO), a meta-heuristic global optimization method, has attracted special interest for its simple algorithm and high searching ability. The updating formula of PSO involves coefficients with random numbers as parameters to enhance diversification ability in searching for the global optimum. However, the randomness makes stability of the searching points difficult to be analyzed mathematically, and the users need to adjust the parameter values by trial and error. In this paper, stability of the stochastic dynamics of PSO is analyzed mathematically and exact stability condition taking the randomness into consideration is presented with an index “statistical eigenvalue”, which is a new concept to evaluate the degree of the stability of PSO dynamics. Accuracy and effectiveness of the proposed stability analysis using the presented index are certified by numerical simulation for simple examples.

2. Theory and Application

The PSO model is given as

\[ v_n^p(k + 1) = \lambda v_n^p(k) + c_1 r_n^p(k) (x_n^{p-best}(k) - x_n(k)) + c_2 r_n^p(k) (x_n^{g-best}(k) - x_n(k)) \]

\[ x_n^p(k + 1) = x_n^p(k) + v_n^p(k + 1) \]

where \( \lambda, c_1, c_2 \geq 0 \), \( r_n^p(k) \) is a unit vector whose argument is \( \theta(k) \). \( x_n^{p-best}(k) \) is the solution of \( p \)-th particle up to discretized time \( k \). \( x_n^{g-best}(k) \) is the global best solution among all particles.

We consider following linear time-varying system in order to show the dynamical characteristics of PSO from the point of view of stability:

\[ p(k + 1) = M(r(k)) p(k), \]

which is form of generalized PSO. \( p(k) = (p_1(k), p_2(k))^T \) and \( r(k) = (r_1(k), \ldots, r_L(k))^T \) are row vectors. \( r(k) \) is given by uniform random numbers in \([0, 1]^L\). \( M \) is a time-varying \( 2 \times 2 \) matrix.

The condition of asymptotic stability of that system is

\[ \lim_{k \to \infty} \|p(k)\| = \lim_{k \to \infty} \left\| \prod_{i=0}^{k-1} M(r(i)) p(0) \right\| = 0. \]

It is difficult to obtain \( p(k) \) because of randomness and non-commutativity of coefficient matrix \( M(r(k)) \). In this paper, we consider Euclid norm of \( p(k) \), and rewrite above condition as a commutative expression:

\[ \|p(k + 1)\| = \left( \prod_{i=0}^{k} \|M(r(i)) q(\theta(i))\| \right) \|p(0)\|. \]

3. Conclusion

In this paper, a new concept of stability analysis for PSO and “statistical eigenvalue” which represents degree of the stability are introduced. Statistical eigenvalue proves efficient for stability analysis of PSO quantitatively.
Genetic Algorithm Sampling the Solution Space Selectively Depending on Difficulty of Power Distribution Network Restoration

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Keywords: smart grid, distribution power network restoration, genetic algorithm, selective sampling

A new genetic algorithm for multi agent based autonomous power distribution network restoration system is proposed. The state of the art of this study is to realize a new genetic algorithm using selective sampling for improving the restoration performance.

Complexity and diversity on the electric power system expect to expand according to the development of distributed generator. However, the existing centralized control method, which is the major architecture of the power system, has a limitation in terms of the scalability and robustness. In order to overcome the limitation, the distributed control approach has a potential to be breakthrough on the future issue. Previous proposed method using contract net protocol succeeded in an effective autonomous control for distributed restoration instead of the legacy centralized control system. In this method, each agent is assigned each area sectioned by switches, If a fault occurs at an area of the network, the agent assigned the area begins to restore procedure to restore the network for reducing the influence of the trouble. In order to realize efficiencies of the procedure, the system applies the contract net protocol (CNP) by which agent exchanges information and acts in concert with other agent. The parameters of CNP are optimized by using genetic algorithm. The GA of previous system uses random sampling for evaluating individuals for improvement of optimization speed. However, there is a difference in difficulty of the restoration in the distribution network, there is a problem that the system recognizes an inferior solution as an excellent solution. That is, individuals might evolve at bad direction by inferior individuals.

In order to overcome the limitation, we propose a new genetic algorithm with selective sampling using difficulty of the restoration for evaluating individuals. This method realizes the selective sampling by a virtual accident selecting algorithm that changes probability of selecting virtual accident area. The virtual accident selecting algorithm consists of weight table and area-value list. The weight table represents a difficulty of restoration in each accident area. The area-value list represents a difficulty of restoration in each accident area. The area-value list represents a difficulty of restoration in latest generation, and effects on weight table in next generation. This architecture enables the system to change the probability of changing each virtual accident area autonomously from restoration simulation.

The simulation system with design tool is developed with the proposed method. The comparison studies and evaluation of performance are conducted. The simulation results (for example Figure 2) show the proposed method achieves to improve the performance.

Fig. 1. Schematic diagram of genetic algorithm sampling the solution space.

Fig. 2. Change of the average of un restoration load against generations in the real scaled distribution model
Evolutional Ant Colony Method Using PSO

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Keywords: evolutionary method, heuristic method, traveling salesman problem, ant colony method, particle swarm optimization

The ant colony method is one of heuristic methods capable of solving the traveling salesman problem (TSP), in which a better tour is generated by the artificial ant’s probabilistic behavior. That is, the ant colony method is characterized by probability for the ant staying in the city to choice the city as the next touring city:

\[ p_{i,j}(t) = \begin{cases} \frac{[\tau_{i,j}(t)]^\alpha [\eta_{i,j}]^\beta}{\sum_{k \in J^m_i(t)} [\tau_{i,k}(t)]^\alpha [\eta_{i,k}]^\beta}, & \text{if } j \in J^m_i(t) \\ 0, & \text{otherwise} \end{cases} \]

and the transition of the pheromone between \( i \)-th and \( j \)-th cities:

\[ \tau_{i,j}(t) \leftarrow (1 - \rho) \cdot \tau_{i,j}(t) + \Delta \tau_{i,j}(t) \]

\[ \Delta \tau_{i,j}(t) = \sum_{m=1}^{M} Q \cdot L^m_i(t), \quad \text{if } (i,j) \in T^m(t) \]

\[ \Delta \tau_{i,j}(t) = 0, \quad \text{otherwise} \]

where \( \tau_{i,j} \) is a quantity of the pheromone between the \( i \)-th and the \( j \)-th cities, \( \eta_{i,j} \) is an inverse of the distance between the \( i \)-th and the \( j \)-th cities, \( J^m_i(t) \) is non-toured cities set of the \( m \)-th ant staying in the \( i \)-th city, \( Q \) is a weighting parameter, and \( L^m_i(t) \) is the length of tour tried to renew the pheromone. However, the generated tour length from the ant colony method depends on the parameters \( (\alpha, \beta, \rho) \) in Eq. (1) and (2) describing the ant’s behavior, and the best parameters corresponding to the problem to be solved is unknown.

In this technical note, firstly, the tour length obtained by the ant colony method with a given combination of parameters \( (\alpha, \beta, \rho) \) is considered a function w.r.t. the parameters \( (\alpha, \beta, \rho) \), which is described as \( L(\alpha, \beta, \rho) \). Then, the problem to find the parameters for the ants to generate the best tour length is formulated as

\[ \min_{(\alpha, \beta, \rho)} L(\alpha, \beta, \rho) \]

\[ \text{subj.to } (\alpha, \beta, \rho) \in X \]

Next, in order to solve the formulated parameter optimization problem, PSO is used as a searching method in the parameter space. Here, the updating process of parameters by PSO is considered as the evolution of the ant’s behavior to adapt to the environment furnished by the problem to be solved.

As simulation results for benchmarks KroA100 and tsp225, Table 1 shows parameters obtained by evolutionary ant colony method (EvAnt) and the corresponding best tour length in comparison with conventional ant colony methods (Ant-keep and Ant-retry). The parameters \( (\alpha, \beta, \rho) \) in EvAnt are the best parameters to adapt to the problem as results of evolution by PSO. The parameters \( (\alpha, \beta, \rho) = (2.00, 5.00, 0.50) \) in conventional methods are recommended values. In simulation, IWA-PSO† is used, in which inertia coefficient is decreased from 0.9 to 0.4 with \( c_1 = c_2 = 2.0 \). Fig.1 shows iteration process of their methods for benchmark tsp225. The results demonstrate effectiveness of the presented evolutionary ant colony methods.

In this technical note, the proposed evolitional method is tested to the duplicate and concentric circle problem with 48 cities, in which the optimal tour is known to be divided into the two types of C-type and O-type solutions with the threshold value of ratio of radii of two circles. In simulation results for the problems with various ratios of radii of two circles, both types of solutions are obtained at trial rate 100% except problems with ratio of radii in a neighborhood of the threshold value.

Table 1. Result of comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>( \rho )</th>
<th>Tour length</th>
</tr>
</thead>
<tbody>
<tr>
<td>EvAnt</td>
<td>2.00</td>
<td>5.00</td>
<td>0.50</td>
<td>22237</td>
</tr>
<tr>
<td>Ant-keep</td>
<td>2.00</td>
<td>5.00</td>
<td>0.50</td>
<td>22237</td>
</tr>
<tr>
<td>Ant-retry</td>
<td>2.00</td>
<td>5.00</td>
<td>0.50</td>
<td>4014</td>
</tr>
<tr>
<td>tsp225</td>
<td>1.46</td>
<td>8.10</td>
<td>0.43</td>
<td>4221</td>
</tr>
<tr>
<td>EvAnt</td>
<td>2.00</td>
<td>5.00</td>
<td>0.50</td>
<td>4221</td>
</tr>
<tr>
<td>Ant-retry</td>
<td>2.00</td>
<td>5.00</td>
<td>0.50</td>
<td>4014</td>
</tr>
</tbody>
</table>

† IWA-PSO means Inertia Weight Approach PSO decreasing inertial coefficient linearly.

Fig. 1. Iteration process of ant colony and proposed method for tsp225
Optimal Control Problem via Self-adaptation Sliding Mode Controller with Neural Network

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Keywords : sliding mode control, self-adaptive sliding mode controller, optimal control problem

1. Introduction
This paper proposes the author’s new Self-adaptation Sliding Mode Controller which added a neural network (SA-SMC+NN) for the optimal control problem. The controlled system is the linear time invariant system and the system parameter and the disturbance are unknown. As minimizing the quadratic cost function, the neural network gives the switching function of the control logic. According to this proposed technique, we can get the constant feedback gain such as the optimal control regulator for this uncertain system based on the control results by SA-SMC+NN.

2. Optimal Control Problem
This paper considers the linear time invariant system

\[ X(t) = AX(t) + Bu(t) + Bd(t) \]  (1)

where \( A \) and \( d(t) \) (disturbance) is unknown, and the quadratic cost function is defined as

\[ J = \int_0^T (X^T Q X + u^T R u) dt \]  (2)

The optimal control regulator is well known as control logic for this problem. The constant feedback gain is

\[ u = KX, \quad K = -R^{-1} B^T P \]  (3)

\( P \) is the solution of the algebraic Riccati equation,

\[ A^T P + PA + Q - PBR^{-1} B^T P = 0 \]  (4)

We must know \( A \) to calculate \( K \), however, \( A \) is unknown, and must examine about the robustness to overcome \( d(t) \).

3. SA-SMC+NN
SA-SMC is expanding in this problem. SA-SMC is a sliding mode control logic which computes the control input only from a state variable and a switching function. It does not need the system parameter and the size of uncertainty such as disturbance.

In this chapter, we consider the second-order linear time invariant system. The user who applies SA-SMC must design the switching function:

\[ \sigma = SX = x_1 x_1 + x_2 x_2 \]  (5)

By the way,

\[ S = -R^{-1} B^T P \]  (6)

is well known as a design method of \( S \) in generally. In this case, we can’t calculate \( P \). Therefore, if SA-SMC can seek the \( S \) minimizing \( J \) by using NN, we are able to get the one of the optimal control regulator because the right side of eq. (7) is the same as eq. (4). This method finds the constant feedback gain such as the optimal control regulator with the following second step.

First Step (The control of the uncertain system): SA-SMC controls the uncertain system, at the same time; NN learns the switching function to minimize the cost function, and outputs the switching function for SA-SMC. Fig. 1 shows the data flow of a two-input system to use in the next chapter as numerical experiment. NN is three layers (input, middle, and output) and the learning’s method is back-propagation method.

Second Step (The choice of the constant feedback gain): After having controlled the system, the gain is provided from the history of \( x_1, x_2 \).

4. Numerical Experiment
Differential game is simulated to confirm the effectiveness of the proposed method.

\[ \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} -0.7 & 0.2 \\ 0.1 & -0.9 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u_1 + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u_2 + \begin{bmatrix} 1 \\ 0 \end{bmatrix} d_1 + \begin{bmatrix} 0 \\ 1 \end{bmatrix} d_2 \]

\[ J = \int_0^T \left( x_1^2 + x_2^2 + R_1 (u_1^2 + u_2^2) \right) dt \]  (7)

Case.1 \( d_1 = 0, \quad d_2 = 0 \)
Case.2 \( d_1 = 0.25, \quad d_2 = 0.25 \)
Case.3 \( d_1 = 0.5 \sin(t), \quad d_2 = 0.5 \cos(5t) \)

5. Conclusion
(1) This control logic doesn’t need the information of the system parameter and the disturbance. (2) Neural network learns the switching function to minimize the quadratic cost function. (3) The constant feedback gain such as the optimal control regulator for this uncertain system is obtained.

Fig. 1. SA-SMC+NN for a two-input system.
Control of Human-Following Robot Based on Cooperative Positioning with an Intelligent Space

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Keywords: intelligent space, mobile robot, position estimation, Extended Kalman filter

This paper proposes the localization method based on interactive communication between a mobile robot and a networked laser range scanner installed in an intelligent space and achieves human-following control of a mobile robot with the method. Generally, human tracking with cameras or laser range scanners on board the robots has been utilized for control of mobile robots to follow human walking. In addition to human tracking, mobile robots have to perform position estimation simultaneously. The proposed system considers to utilize an intelligent environment where sensors are distributed in order to obtain positions of human and robot.

The proposed system as shown in Fig. 1 exchanges position and heading information estimated in the mobile robot and the networked laser range scanner with each other. The networked sensor searches and detects target human and the robot based on the position information sent from the robot. The robot receives the detection results from the networked sensor. Then, the estimate position is updated and reference velocities for human-following control are calculated with them. Generally, odometry based position estimation of the robot accumulates errors over time. On the other hand, the networked sensor installed in the intelligent environment cannot continue to track all objects without losing them because of occlusion. The proposed system compensates mutual position information for estimation errors with odometry in the robot and unstable tracking of target in the networked sensor.

There are several issues for achievement of the proposed system. One is sensor fusion for position update of the robot. The proposed system applies retroactive sensor fusion between the robot and the networked sensors in order to address network time delay and sensing time lag. The other is communication timing between the robot and the networked sensors while human-following. The robot has to communicate to the networked sensors before increase of position estimation errors. And it is desirable not to communicate so frequently for avoiding that a specific robot dominates the networked sensor. Position request based on estimation uncertainty of the robot is introduced in the proposed system.

Human-following experiments are performed and the results that include human detection and position estimation of the robot are shown as shown in Fig. 2.
Implementation of BFA (Backtrack Free Path Planning Algorithm) for 3 Dimensional Work Spaces and its Application to Path Planning of Multi Manipulators

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Keywords : manipulator, backtrack free, path planning, exact algorithm

To simplify the representations of attitudes of manipulators consists of multiple links, almost all existing path planning algorithms use the Configuration space (C-space) that is constituted by a set of moving angles of individual links(1). By using the C-space path planning is formulated as a problem to find paths in the high dimensional space in which a point moves while avoiding obstacles. However, because the dimension of the C-space becomes high for manipulators with many links, currently available resolution complete path-planning algorithms cannot be applied to practical applications. Their computation time and memory space for calculating collision free paths increase exponentially with the number of links. Therefore, in many cases, heuristics were introduced, and consequently they are not back-track free, and there are cases where they cannot find paths even they exist. Also it is difficult to estimate times necessary for path calculations. To overcome the above difficulty BFA had been proposed(2).

Different from many existing path planning algorithms, BFA searches paths in 2 or 3-dimensional work spaces directly, in order to reduce the huge computation volume caused by the high dimensionality of C-spaces. Compared with the C-space where the dimension increases with the number of links, the dimension of the work space is fixed at 2 or 3. Therefore when loci of individual links can be calculated sequentially without any backtrack, it is possible to construct an algorithm, of which computation volume is proportional to the number of links. BFA achieves just this. In BFA, positions of manipulators in the workspace are approximated by finite number of grid points, and provided that grid sizes are small enough, BFA determines the existence of paths correctly, and if they exist, it finds paths of individual links sequentially from the top to the base links without any backtrack, i.e. BFA is resolution complete.

This paper discusses implementation issues of BFA in 3-dimensional work spaces, and proposes methods for avoiding collisions among links themselves that are allowed in the original algorithm. Also BFA is extended to the algorithm for path planning of multiple manipulators cooperating with each other to achieve complicated tasks. One of advantages of using BFA for multi manipulators is that paths of individual manipulators can be calculated almost completely in parallel. Simulation based experimentations in which 3 manipulators performed in environments such as shown in Fig. 1 showed that the extension could find paths efficiently enough. Computation volume was almost exactly proportional to the number of links as shown in Fig. 2. Fig. 3 is an environment where BFA performance was compared with that of ATACE(3). According to the comparison BFA could generate paths more than 20 times faster than ATACE even when the number of links is suppressed at a small value i.e. 3.

References

A Trial for the Management of Email Delivery Delay Problem Associated with Spam Mails Filtering in University

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Keywords : spam mail management, email delivery

1. Introduction

Electronic mail (email) system has been established as a typical and the most important tool for global communications. Nowadays, the system plays essential roles in education, research, and management of the university. The number of users and the rate of utilization of the email system are increasing apparently. On the other hand, huge numbers of emails are delivered from the Internet, and many users get emails, in which almost of all accepted emails are spam mails. There are about 6,000 users in Yamaguchi University that receive emails in a day. Total accepted emails are 300 thousands in a day. If the total emails delivered from the Internet are filtered after accepted, SMTP (Simple Mail Transfer Protocol) server must deliver 10 times as many as emails that should be delivered. In other words, it is supposed that 80-90% of total accepted emails are spam mails. Thus, SMTP server deliver waste emails such as spam mails. Huge numbers of spam mails bring situations of not only hard to find the necessary email but also happening to delay delivery of emails.

Many methods for spam mails filtering have been proposed, and it was classified into several kinds as follows.
1. A method based on a process of email delivering system.
2. A method based on the contents of email.
3. A method based on the information of appended email header.

It is well known that these methods have respective problems. The second method is superior to the others in terms of reducing the number of false positives and negatives, and the method allows users to change the accuracy rate of a classification. However, the first method is superior to the others in terms of delivery delay of emails, because this method can classify the spam mails before delivering their mail body to the recipient.

There are two well-known strategies for spam mails filtering. One is the greylisting method which pays attention to not re-send almost all spam mails, and the other is a method based on SMTP server name which was not reverse-resolved by DNS (Domain Name System). These strategies can not classify the email correctly in case that the SMTP server has wrong setting. There are several methods for spam mails filtering based on key words search in the email, which utilize extracting the feature of the email and classification by the recipient. In these methods, a criterion for filtering has to be set and to be renovated customarily. It has the advantage of enabling each user to change setting parameters such as the accuracy rate of classification and whether filtering system is adopted or not. There is no ideal system that can filter only spam mails. There are risks of error such that the correct mail classified into the spam mail (false positive) and the spam mail classified into the correct mail (false negative). We really may not find these risks of error.

Diffs from corporation, the university has a special circumstance and a culture of independency and freedom as a policy of email system to support wide range activities in education and research. The majority of university staff requests the introduction of spam mail filtering system, but the minority does not want. There have been several trials to realize spam mail filtering system in university. Most of the university, which constructed the spam mail filtering system, applied the same method to all members of the staff without reaching a consensus on the problem. There is little university adopting the filtering system only for applicants who want to introduce the system. Other universities, that do not introduce the spam mail filtering system, encounter several problems caused by a flood of spam mails.

In this paper, we report on a trial for the management of email delivery delay problem associated with the introduction of spam mail filtering system only for applicants who want to adopt the filtering. Since September 2006, as a result of an enduring effort to unify the mail server in our university, we have been provided a spam mail filtering system for applicants. However, the delivery delay of emails has become obvious owing to introduce the spam mail filtering system, and the time of delivery delay of an email was more than half a day according to the circumstances. On November 2007, a refuse process (reservation) was applied to the email to reduce the delivery delay. We can summarize the results of our trial in this study as follows:

1. Spam mail measures are substantially unnecessary for users receiving less than 10 mails/day (about 87% recipients).
2. Effective spam mail measures can be achieved by applying the proposed method only to little applicants (12% heavy users).
3. The mail delivery delay was caused by the existence of unknown addresssee emails that request repeated retransmission (about 90% of total transmission process).
4. The mail delivery delay can be effectively avoided by reducing the delivery of unnecessary emails sending from the outside of university.
5. Mailing lists under improper sender management and operational administrative existed (about 30% of total mailing lists). A lot of emails transmitted by way of the mailing lists server were the spam mails (about 2/3 emails). It is also important to keep the appropriate operational administrative of the mailing list to reduce the mail delivery delay.