

## Introduction In

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linear  
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tive  
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tions.  
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Swarm  
Op-

global  
op-  
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mum,  
the  
other  
fishes  
con-  
verge  
to  
the  
fish  
[?].  
Mean-  
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there  
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other  
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rithm  
called  
Fire-  
fly  
Al-  
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rithm  
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which  
is  
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larly  
well  
to  
lo-  
cal  
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with  
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ing  
light  
of  
fire-  
flies  
[?].  
In  
two  
fire-  
flies,  
a  
brighter  
fire-  
fly  
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tracted  
the  
other  
one.  
Al-  
though  
these  
al-  
go-  
rithms  
are  
widely  
used  
for  
op-  
ti-  
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prob-  
lem,

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tion  
 $x_*$ ,  
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tion  
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ward,  
each  
bat  
moves  
to  
lo-  
ca-  
tion  
 $x_i$   
with  
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ity  
 $v_i$   
to-  
ward  
global  
best  
so-  
lu-  
tion,  
as  
shown  
in  
Fig.  
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search  
step,  
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a  
new  
so-  
lu-  
tion  
 $x_{new}$   
around  
global  
best  
so-  
lu-  
tion,  
as  
shown  
2nd  
phase  
of  
Fig.  
??.  
The  
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tion  
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tance  
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each  
bat  
away.  
The  
dis-  
tance  
equa-  
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ten  
as  
be-  
low.

$$(8) \quad d_i^{t-1} = 1/K \sum_{j=1}^K (x_{i*} - x_j^{t-1})$$

$$(9) \quad d_i^{t-1} = 1/K \sum_{j=1}^K (x_i^{t-1} - x_j^{t-1})$$

K  
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 $x_{i*}$   
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NN  
is  
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and

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ment,  
but  
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ing  
on  
num

Pop-  
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 tion  
 $x_i(i =$   
 $1, 2, ..., n)$   
 and  
 $v_i$   
 Define  
 fre-  
 quency  
 $f_i$   
 at  
 lo-  
 ca-  
 tion  
 $x_i$   
 Initialize  
 pulse  
 rates  
 $r_i,$   
 and  
 loud-  
 ness  
 $A_i$   
 $(t <$   
 Max  
 num-  
 ber  
 of  
 it-  
 er-  
 a-  
 tions)  
 i=1  
 to  
 n  
 Gen-  
 er-  
 ate  
 new  
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 tions  
 $x_i$   
 by  
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 ing  
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 quency  
 $f_i$   
 Up-  
 date  
 lo-  
 ca-  
 tion  
 $x_i,$   
 ve-  
 loc-  
 ity  
 $v_i$   
 $[eqs.(??)(??)(??)]$   
 and  
 k-  
 NNBA  
 for  
 $[eq.(??)(??)]$   
 NSBA  
 for  
 $[eq.(??)(??)]$   
 $(rand >$   
 $r_i)$   
 Gen-  
 er-  
 ate  
 a  
 new

in  
any  
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bors.

Comparison

with  
II  
and  
VI  
On  
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is  
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most  
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ter  
than  
k-  
NNBA  
in  
each  
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cept  
for  
K=4,  
dist  
of  
k-  
NNBA  
is  
a  
bit  
smaller.

Over-  
all,  
*dist*  
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higher  
than  
the  
other  
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ods  
on  
griewank  
func-  
tion.  
In  
ras-  
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ri-  
gin  
func-  
tion,  
k-  
NNBA  
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ally  
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creased.  
How-  
ever,  
NSBA  
slowly  
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creased  
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til  
K=16.

Comparison

with