Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics. Volume I: Foundations

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ISBN 83-894-7540-5

Dedicated to Professor Beloslav Riečan on his 75th anniversary

Generalized net of a genetic algorithm with intuitionistic fuzzy selection operator

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Abstract

Using the apparatus of Generalized nets a generalized net model of a genetic algorithm with intuitionistic fuzzy selection operator is developed. Selection operator is one of the basic genetic algorithm operators. It gives a direction to evolution, conserves successful states, but at the same time it reduces the diversity of the population. The proposed intuitionistic fuzzy operator aims to prevent some demerits of the genetic algorithms performance. It is known that "the best" chromosome does not always keep on improving in each generation. In the presented generalized net model intuitionistic fuzzy selection operator decreases the possibility for chromosome aggravation giving the chance the best solution from the current generation will be superior to or at least the same as the past.

Keywords: generalized net, genetic algorithm, intuitionistic fuzzy logic, selection operator.

1 Introduction

The popularity of genetic algorithms (GAs) [9] has grown a lot under recent years and they have been applied to a wide range of problems [13, 22]. The different GAs have different features in order to solve different type of problems. The GAs can be configured in many ways, and these different setups can have strong effects on the solutions found. Fitness functions; crossover, mutation, selection and reinsertion operators; and population size are just a few of the many parameters that are available to be optimized. There are a lot of papers on various techniques researchers have found to set up these parameters for various problem domains [6, 7, 8, 10, 11, 13, 14, 18, 22].

Generalized Net (GN) models [2] related to the GA is a concept that promises a lot. Up to now, using the apparatus of GN a few GN model regarding GA performance were developed. The first GN model describes the GA search procedure [1, 3]. The GN model simultaneously evaluates several fitness functions, ranks the individuals according to their fitness and chooses the best fitness function with regards to the specific problem domain. The second GN model related to the GA is developed for evaluation of the algorithm fitness function [19]. Performing series of experiments the presented GN model could be defined the "best" fitness function for each considered problem domain. The net tests the effect that the different fitness functions have on GA performance and proposes such fitness function that enhances the algorithm's efficiency. The next GN model presented in [21] is an extension of the GN model in [19]. The net has the capability to test different groups of the defined GA operators and to choose the most appropriate combination among them.

The apparatus of GN is also applied to a description of different functions for selection operator [15, 16]; for mutation operator [20] and for crossover operator [17].

A genetic operator is a process used in GA to maintain genetic diversity. Genetic variation is a necessity for the process of evolution. Genetic operators used in AG are analogous to those which occur in the natural world: survival of the fittest, or selection; asexual or sexual reproduction (crossover, also called recombination); and mutation.

Selection is clearly an important genetic operator. The selection of individuals to produce successive generations plays an extremely important role in a genetic algorithm. A probabilistic selection is performed based upon the chromosome's fitness such that the better individuals have an increased chance of being selected. An individual in the population can be selected more than once with all individuals in the population having a chance of being selected to reproduce into the next generation. There are several schemes for the selection process: *roulette wheel selection* and its extensions, *scaling techniques*, *tournament*, *elitist models*, and *ranking methods* [12, 13, 14].

In this work a GN of a GA with Intuitionistic fuzzy selection operator is proposed. Intuitionistic fuzzy logic (IFL) and Intuitionistic fuzzy sets (IFS) have gained a wide recognition as a useful tool for modeling uncertain phenomena. The proposed intuitionistic fuzzy selection operator aims to prevent some demerits of the GA performance. The reproduction in GA is considered for determining which chromosomes will be chosen as the basis of the next generation. Although various preserving strategy is used to guarantee the survival of the most fitted chromosome from population into the matting pool, the results may deteriorated.

2 Intuitionistic fuzzy selection operator

The IFS are defined as extensions of the ordinary fuzzy sets [4]. All results which are valid for the fuzzy sets can be transformed here, too. Also, all researches, for which the apparatus of the fuzzy sets can be used, can be described in the terms of the IFS.

Let a set E be fixed. An IFS A in E is an object of the following form [5]:

$A =< x, \mu_A(x), \nu_A(x) > |x \in E,$

where functions $\mu_A : E \to [0, 1]$ and $\nu_A : E \to [0, 1]$ define the degree of membership and the degree of non-membership of the element $x \in E$, respectively, and for every $x \in E$:

$0 \leq \mu_A(x) + \nu_A(x) \leq 1.$

Let

$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x).$

Therefore, function π_A determines the degree of uncertainty.

Considering selection operator in the GA it can be assigned intuitionistic upper and lower limits, F_{upper} and F_{lower}, considering the fitness function (F) of the chromosome. Therefore, if the fitness function does not fall between these limits, i.e. is $F_{lower} \leq F \leq F_{upper}$, then it can not be determined unambiguously whether it is a "good results" or "poor results". Conversely, values outside the intuitionistic limits can be unambiguously assigned to one of the two categories. Therefore the following membership functions are defined:

for $\mu_A :\ F_{upper} < F$

for $\nu_A :\ F \leq F_{lower}$

for $\pi_A :\ F_{lower} < F < F_{upper}$

There could be considered three possible selection strategies:

Strategy 1. Chromosomes are ranked according above listed membership functions. First are set these chromosomes that have fitness function bigger than F_{upper}, next are the individuals that are between the interval [F_{lower}, F_{upper}], and finally the individuals that have fitness function lower than F_{lower}. According defined parameter generation gap part of the last group of chromosomes will not be selected for the new population.

Strategy 2. Chromosomes that will be selected for the new population are these with the fitness function bigger than F_{upper} and/or chromosomes with fitness function between the interval [F_{lower}, F_{upper}]. The chromosomes that have fitness function lower than F_{lower} will not be selected and copied into the new population. The population size is restored by the multiplying of the first or first two individuals.

Strategy 3. Only chromosomes that belong to membership function is selected and copied into the new population. The population size is restored by the multiplying of these chromosomes.

Thus selected and copied chromosomes are then process applying operators crossover and mutation.

3 Generalized net model

The proposed GN model is based on model presented in [19]. It consists of four contours (see Fig. 1). Tokens from type α describing individuals (solutions) move in the first of them (the l-contour). A single β-token, describing the algorithm itself, moves in the second (the m-contour). A γ-token for each β-token loops in the third (the n-contour). The γ-token controls the set of algorithm operators and fitness functions.

Initially, α-tokens representing individuals in terms of the genetic algorithms theory [12] enter place l_1. They have the following initial characteristic:

$$x_0^{\alpha} = \text{“}\langle I, C, f\rangle\text{”},$$

where $I \in \mathcal{N}$ is the identifier of the individual;
C is the chromosome of the individual;
$f \in \mathcal{R}$ is the individual fitness.

Together with the α-tokens, a single β-token enters m_1. It has as a characteristic the parameters of the genetic algorithm.

$$x_0^{\beta} = \text{“}\langle Task, NIND, XOVR, MUTR, GGAP\rangle\text{”},$$

where
$Task \in \{\text{“}estimate\text{”}, \text{“}select\text{”}, \text{“}process\text{”}, \text{“}reinsert\text{”}, \text{“}store\text{”}\}$;

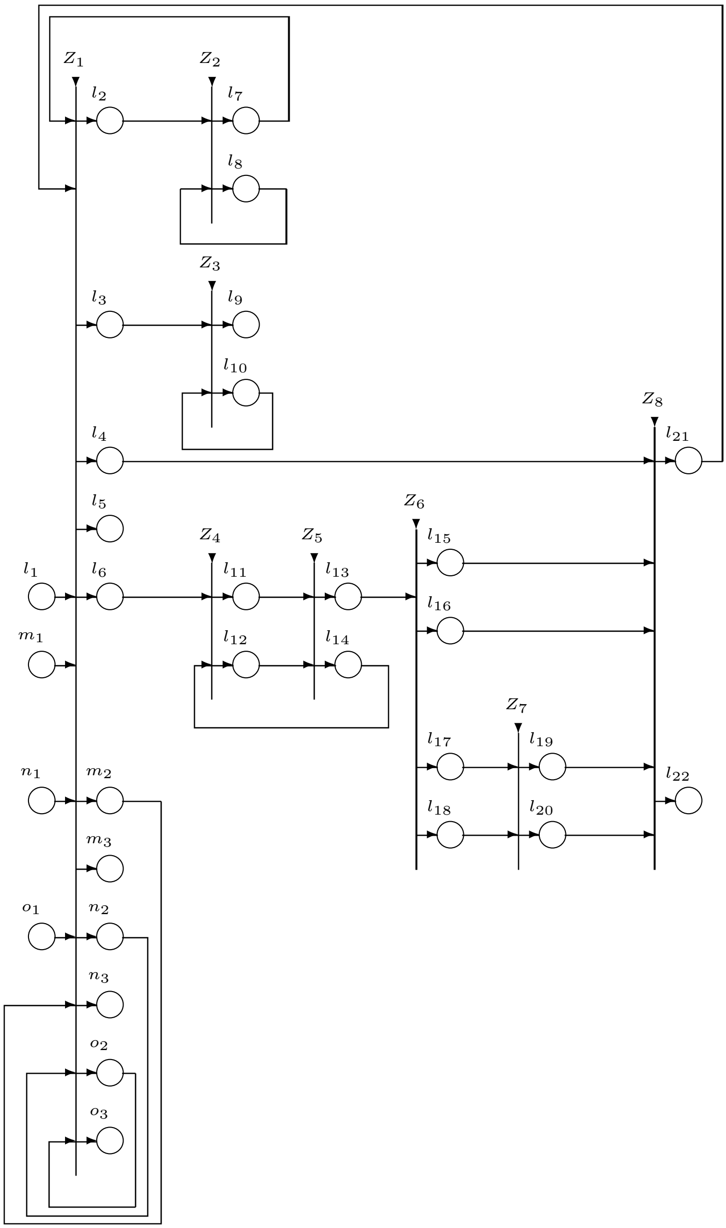

Figure 1: GN model

$NIND \in \mathcal{N}$ is the number of the individuals controlled by the algorithm;
$XOVR \in [0, 1]$ is the probability of crossover;
$MUTR \in [0, 1]$ is the probability of mutation;
$GGAP \in [0, 1]$ is the generation gap.

Together with the α-tokens, another single γ-token enters n_1. It has as a characteristic the parameters of the genetic algorithm.

$$x_0^\gamma = \text{“}\langle FF, CROS, MUT, SEL, REINS\rangle\text{”},$$

where
$FF = \{f/f : U_C \to \mathcal{R}\}$ is a set of fitness functions. Where U_C is the set of all chromosomes;
$CROS = \{c/c : U_C \to \mathcal{R}\}$ is a set of crossover functions;
$MUT = \{m/m : U_C \to \mathcal{R}\}$ is a set of mutation functions;
$SEL = \{s/s : U_C \to \{\text{“}survive\text{”}, \text{“}die\text{”}, \text{“}mutate\text{”}, \text{“}crossover\text{”}\}\}$ is a set of the selection function that determines what will happen with the individual;
$REINS = \{r/r : U_C \to \{\text{“}false\text{”}, \text{“}true\text{”}\}\}$ is a set of the reinsertion function that determines how the offspring inserts in the current population.

For each β- and γ-tokens one δ-token enters the net in place o_1. This token describes the process that controls the execution of the genetic algorithm. The δ-token characteristic has the following form:

$$x_i^\delta = \text{“}\langle T, M, E\rangle\text{”},$$

where
T is an estimation of the total efficiency of the algorithm;
M is function that selects genetic operators (crossover, mutation and reinsertion) and intuitionistic fuzzy selection strategy;
E is the end-condition function that determines whether the algorithm will terminate its execution.

For each step of the algorithm the β-, γ and δ-tokens loop in m_2, n_2 and o_2, respectively.

All α-tokens gather in l_2 where the value of fitness function for the individual is updated, i.e. field f from their characteristic:

$$pr_3(x_i^\alpha) = pr_4(x_{cu}^\beta, x_{cu}^\gamma)(pr_2(x_i^\alpha)).$$

After evaluation of the definite set of fitness functions the individuals are selected for survival or death, crossover and mutation. The probability for a given action is determined by the fitness value of the individual and the probability of the operations.

Transition Z_1 has the following formal definition:

$$Z_1 = \langle \{l_1, l_7, l_{21}, m_1, m_2, n_1, n_2, o_1, o_2\}$$

$$\{l_2, l_3, l_4, l_5, l_6, m_2, m_3, n_2, n_3, o_2, o_3\},$$

$$r_1, \wedge(\vee(l_1, l_7, l_{21}), \vee(m_1, m_2), \vee(n_1, n_2), \vee(o_1, o_2))\rangle,$$

where

$$r_1 = \begin{array}{c|ccccccccccc}
 & l_2 & l_3 & l_4 & l_5 & l_6 & m_2 & m_3 & n_2 & n_3 & o_2 & o_3 \\
\hline
l_1 & W_1 & W_2 & W_3 & W_4 & W_5 & F & F & F & F & F & F \\
l_7 & W_1 & W_2 & W_3 & W_4 & W_5 & F & F & F & F & F & F \\
l_{21} & W_1 & W_2 & W_3 & W_4 & W_5 & F & F & F & F & F & F \\
m_1 & F & F & F & F & F & W_6 & \neg W_6 & F & F & F & F \\
m_2 & F & F & F & F & F & W_6 & \neg W_6 & F & F & F & F \\
n_1 & F & F & F & F & F & F & F & W_7 & \neg W_7 & F & F \\
n_2 & F & F & F & F & F & F & F & W_7 & \neg W_7 & F & F \\
o_1 & F & F & F & F & F & F & F & F & F & W_8 & \neg W_8 \\
o_2 & F & F & F & F & F & F & F & F & F & W_8 & \neg W_8
\end{array},$$

and

$W_1 =$ “$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) = 'estimate'$ ”,

$W_2 =$ “$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) = 'store'$ ”,

$W_3 =$ “$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) =' select')$”&“$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma})(pr_2(x_i^{\alpha})) =' survive')$”,

$W_4 =$ “$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) = 'select')$” & “$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma})(pr_2(x_i^{\alpha})) = 'die')$”,

$W_5 =$ “$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) = 'select')$” & “$(pr_4(x_{cu}^{\beta})(pr_2(x_i^{\alpha})) = 'crossover')$”,

$W_6 =$ “$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) \neq \emptyset$”,

$W_7 =$ “$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) \neq \emptyset$”,

$W_8 =$ “$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) \neq \emptyset$”.

The form of the transition Z_2 is:

$$Z_2 = \langle \{l_2, l_8\}, \{l_7, l_8\}, r_2, \wedge(l_2, l_8) \rangle,$$

where

$$r_2 = \begin{array}{c|cc} & l_7 & l_8 \\ \hline l_2 & false & W_9 \\ l_8 & \neg W_9 & W_9 \end{array},$$

where
$W_9 =$ "$pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) = 'process'$ ".

In position l_7 the individuals are ranked in groups according to their fitness. Depending on the accepted intuitionistic fuzzy selection strategy the generalized net will operate over different groups.

The form of transition Z_3 is:

$$Z_3 = \langle \{l_2, l_8\}, \{l_7, l_8\}, r_2, \wedge(l_2, l_8) \rangle,$$

where

$$r_2 = \begin{array}{c|cc} & l_9 & l_{10} \\ \hline l_3 & false & W_9 \\ l_{10} & \neg W_9 & W_9 \end{array},$$

where W_9 is defined above.

The individuals that can "survive" without changes in their chromosomes are represented by α-tokens in place l_4. According to the Intuitionistic Fuzzy selection operator and to the value of the reinsertion function (generation gap) they will either "survive" and transfer to l_{21} or will "die" and leave the net via l_{22}.

The individuals that can "die" are represented by α-tokens in place l_5.

The individuals chosen for the crossover operation are represented by a set of α-tokens in place l_6. All of them transfer into l_{11} and obtain no new characteristics. After that the corresponding tokens of chosen couples of individuals unite in l_{13} and the rest of the tokens transfer in l_{14}. Tokens from l_{14} return back to l_{12} in order to participate in the choice of the next couples.

In the case of a one-point crossover operation united tokens from place l_{13} will split into two-"parent" individuals, represented by α-tokens in l_{15} and l_{16}, and two "child" individuals represented by tokens in l_{17} and l_{18}, respectively. After each step of that loop new "child" individuals are reproduced in l_{17} and l_{18}. The "child" individuals are mutated and the results is represented by tokens in l_{19} and l_{20}.

The forms of the transitions Z_4, Z_5 and Z_6 are:

$$Z_4 = \langle \{l_6, l_{14}\}, \{l_{11}, l_{12}\}, r_4, \vee(l_6, l_{14}) \rangle,$$

where

$$r_4 = \begin{array}{c|cc} & l_{11} & l_{12} \\ \hline l_6 & W_9 & false \\ l_{14} & false & true \end{array},$$

where W_9 is defined above.

Based on the stored information of the previous model states the M function could be defined the next group of the genetic algorithm operators. The information for the appropriate fitness function could be take from the stored information in the place l_8.

$$Z_5 = \langle \{l_{11}, l_{12}\}, \{l_{13}, l_{14}\}, r_5, \vee(l_{11}, l_{12}) \rangle,$$

where

$$r_5 = \begin{array}{c|cc} & l_{13} & l_{14} \\ \hline l_{11} & W_9 \& W_{10} & W_9 \& \neg W_{10} \\ l_{12} & W_9 \& W_{10} & W_9 \& \neg W_{10} \end{array},$$

where
$W_{10} =$ "the individuals are in suitable pairs".

$$Z_6 = \langle \{l_{13}\}, \{l_{15}, l_{16}, l_{17}, l_{18}\}, r_6, \vee(l_{13}) \rangle,$$

where

$$r_5 = \begin{array}{c|cccc} & l_{15} & l_{16} & l_{17} & l_{18} \\ \hline l_{13} & W_{11} & W_{11} & W_{11} & W_{11} \end{array},$$

where
$W_{11} =$ "the operation is one point crossover".

The α-tokens (new "child" individuals) chosen for mutation transfer from positions l_{17} and l_{18} to positions l_{19} and l_{20} and obtain as a characteristic the new chromosome description:

$$x_i^{\alpha} = \text{"}\langle I, C', f \rangle\text{"},$$

where C' can be the result of one, two or multi-point mutation or, in general, any operation with an argument being a single individual chromosome. This transformation is represented by transition:

$$Z_7 = \langle \{l_{17}, l_{18}\}, \{l_{19}, l_{20}\}, r_7, \vee(l_{17}, l_{18}) \rangle,$$

where

$$r_7 = \begin{array}{c|cc} & l_{19} & l_{20} \\ \hline l_{17} & W_{12} & false \\ l_{18} & false & W_{12} \end{array},$$

where
$W_{12} =$ "the operation is mutation".

Now all α-tokens that represent individuals including the new offspring are the input places of transition Z_8. The reinsertion function will determine which of them will remain in the population and which of them will not. Tokens that represent survived individuals enter place l_{21}; the rest of the tokens leave the net via place l_{22}.

$$Z_8 = \langle \{l_4, l_{15}, l_{16}, l_{19}, l_{20}\}, \{l_{21}, l_{22}\}, r_8, \vee(l_4, l_{15}, l_{16}, l_{19}, l_{20}) \rangle,$$

where

$$r_8 = \begin{array}{c|cc} & l_{21} & l_{22} \\ \hline l_4 & W_{13} & \neg W_{13} \\ l_{15} & W_{13} & \neg W_{13} \\ l_{16} & W_{13} & \neg W_{13} \\ l_{19} & W_{13} & \neg W_{13} \\ l_{20} & W_{13} & \neg W_{13} \end{array}$$

where
$W_{13} =$ “$(pr_4(x_{cu}^{\beta}, x_{cu}^{\gamma}) =' reinsert')$” & “$(pr_6(x_{cu}^{\beta})(pr_2(x_i^{\alpha})))$”.

4 Conclusion

A GN model of a GA with intuitionistic fuzzy selection operator is developed. The aim of the proposed GN model is to prevent some demerits of GA. The fuzziciation of the chromosomes fitness intend to achieve the best solution from the current generation and this solution will be superior to or at least the same with the past.

As a further research in the presented here GN different combination between genetic operators (selection, crossover and mutation) will be investigated. Using selection operator alone will tend to fill the population with copies of the best chromosome from the population. Using selection and crossover operators will tend to cause the algorithms to converge on a good but sub-optimal solution. Using mutation alone induces a random walk through the search space, while using selection and mutation creates a parallel, noise-tolerant, hill-climbing algorithm. It is worth testing these opportunities to find reasonable settings for the problem class being worked on.

Acknowledgements

This work is partially supported by National Science Fund Project No DID-02-29 Modeling Processes with Fixed Development Rules (ModProFix).

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The papers presented in this Volume 1 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Tenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2011) organized in Warsaw on September 30, 2011 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

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The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Tenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2011) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

ISBN-13 9788389475404
ISBN 838947540-5
9 788389 475404