# Generating Reactive Robots' Behaviors using Genetic Algorithms

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Abstract: In this paper, we analize and benchmark three genetically-evolved reactive obstacle-avoidance behaviors for mobile robots. We buit these behaviors with an optimization process using genetic algorithms to find the one allowing a mobile robot to best reactively avoid obstacles while moving towards its destination. We compare three approaches, the first one is a standard method based on potential fields, the second one uses on finite state machines (FSM), and the last one relies on HMM-based probabilistic finite state machines (PFSM). We trained the behaviors in simulated environments to obtain the optimizated behaviors and compared them to show that the evolved FSM approach outperforms the other two techniques.

## 1 INTRODUCTION

In the many years of research on robot navigation several algorithms for robot exploration in unknown environments have been proposed, many of them based on Finite State Machines (FSM) (Fraundorfer and Scaramuzza, 2012). In these algorithms, a robot with negligible errors in both, the sensor readings and its motion, under the same initial conditions, should behave always in the same way due to the deterministic nature of its control algorithm.

While this behavior fits most applications, the exploration of new environments makes desirable for the robot to behave differently every time under similar conditions (for example, to construct a complete map of a scene by aggregating unexplored areas). Therefore a probabilistic finite state machine is used. Consequently, we built these state machines using a modified version of Hidden Markov Models (HMM) and we proposed an optimization process to find the best HMM model using Genetic Algorithms (GA).

The paper is organized as follows: in Section 2 we present the related work in this area. Section 3 presents the standard robot behavior of potential fields to be compared with the behaviors proposed in this paper. Meanwhile, in Section 4 we detail how to create navigation behaviors using FSM. Then, in Section 5 we present the Probabilistic Finite State Machines (PFSM) using HMM. Further, in Section 6 we explain how we got the fittest behaviors for the potential fields approach, the FSM and the PFSM using Genetic Algorithms. Finally, in Section 7 we detail the experiments and results, and close in Section 8 with the conclusions of this work.

## 2 RELATED WORK

Brooks proposed a new robotics paradigm to control robots in which their behaviors are built using Augmented Finite State Machines (AFSM) (Brooks, 1986). To Brooks, by connecting together the AFSM, each one containing a behavior, emergent intelligence can be achieved by a robot.

Simulated emergent patterns from a collection of artificial agents refers back to Barricelli (1954). In this work, as refereed by Fogel (2006), Barricelli simulates an early version of cellular automaton in which numbers, that live in one and two dimensional worlds, interact following simple rules. His computer simulations showed that such simple rules are sufficient to give rise to regular patterns which he called "organisms".

Meanwhile, starting in 1962, Lawrence J. Fogel and colleagues successfully applied artificial evolution algorithms to the problem of finding predictions in sequences of symbols in finite alphabets (Fogel,



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2006). In their work, they used finite state machines to represent the behavior of the agent (Fogel, 2006). This early evolutionary algorithm uses a population of states machines and exploits several kinds of mutations to generate the offspring. The task to solve was to predict whether the next number in a sequence will be a prime number or not. The algorithm quickly learned to discriminate even numbers and numbers divisible by three as non-prime and achieved a 78% of prediction accuracy.

In (Negrete et al., 2018), from a red, green, blue and distance (RGBD) sensor, as the Kinect, a different map representation is used where the free space is divided into regions using vector quantization where each centroid represents a node in a topological map useful for robot navigation, where quantization has been proven to be the state-of-the-art for scaling the search space (Guo et al., 2020). A probabilistic map representation has been proposed in (Savage et al., 2018) where we represent the current pose with a Hidden Markov Model and determine the next navigation node by incorporating new laser readings and the all trajectory information into the model; therefore, although reactive, this approach produces smooth trajectories. Probabilistic representation given by a Hidden Markov Model from a number of sensor readings and robot displacements have been proven useful for robot localization and navigation (Shahriar and Zelinsky, 1999), (Shahriar and Zelinsky, 2014), and (Mohanan and Salgaonkar, 2020). Furthermore, path planning in mobile robots is a very well known problem and Genetic Algorihms have been widely applied to solve this problem (Yakoubi and Laskri, 2016) and (Yakoubi and Laskri, 2018).

# 3 ROBOT BEHAVIORS USING POTENTIAL FIELDS

In this type of behavior, the robot is modeled as a particle that is under the influence of two potential fields, one attracts it towards the destination, while another takes him away from obstacles (Latombe et al., 1991). Obstacles exert repulsive forces, while the goal destination generates and attraction force. The robot moves through a potential field on the steepest slope until it brings it to the destination.

The robot position in the environment is $\overline{q}_n = [x_n, y_n]$, and the potential field exerted on the robot at that point is:

$$U(\overline{q}) = U_{atr}(\overline{q}) + U_{rep}(\overline{q})$$

the gradient of the potential field:

$$\overline{F}(\overline{q}) = \nabla U(\overline{q}) = \left(\frac{\partial U}{\partial x}\,\hat{\imath} + \frac{\partial U}{\partial y}\,\hat{\jmath}\right)$$

using the "steepest descent" technique the next position of the robot is given by:

$$\overline{q}_n = \overline{q}_{n-1} - \delta_i \overline{f}\left(\overline{q}_{n-1}\right)$$

where $\delta_i$ are constants that determine the size of the robot advance, sometimes it remains fixed.

$\overline{f}\left(\overline{q}_{n-1}\right)$ is a unit force vector in the direction of the gradient:

$$\overline{f}(\overline{q}_{n-1}) = \frac{\overline{F}(\overline{q}_{n-1})}{|\overline{F}(\overline{q}_{n-1})|}$$

The robot moves following the steepest slope of the potential field, given by the forces of attraction and repulsion:

$$\begin{aligned}\overline{F}(\overline{q}_{n-1}) &= \overline{F}_{atr}(\overline{q}_{n-1}) + \overline{F}_{rep}(\overline{q}_{n-1})\\ \overline{q}_n &= \overline{q}_{n-1} - \delta_i \overline{f}\left(\overline{q}_{n-1}\right)\end{aligned}$$

## 3.1 Attraction Field

The destination that the robot needs to reach is:

$$\overline{q}_{dest} = (x_{dest}, y_{dest})$$

We define the attractive field of parabolic type as:

$$U_{atr}(\overline{q}) = \frac{1}{2}\varepsilon_1 \left|\overline{q} - \overline{q}_{dest}\right|^2$$

where $\varepsilon_1$ it is a constant that modulates the field and is found empirically. The attractive force in $\overline{q}$ is:

$$\nabla U_{atr}(\overline{q}) = \varepsilon_1[\overline{q} - \overline{q}_{dest}] = F_{atr}(\overline{q})$$

## 3.2 Repulsive Fields

We define the repulsive field as:

$$U_{rep}(q) = \frac{1}{2}\eta\left(\frac{1}{|\overline{q} - \overline{q}_{obs}|} - \frac{1}{d_0}\right)^2$$

where $\overline{q}_{obs} = (x_{obs}, y_{obs})$ is the obstacle centroid position. This repulsion field applies when $|\overline{q} - \overline{q}_{obs}| \leq d_0$. Otherwise, it is considered that the obstacle does not generate any repulsive force because it is too far away. Where $\eta$ is a constant that modulates the field and is found empirically. Then the potential field is:

$$\nabla U_{rep}(\overline{q}) = -\eta\left(\frac{1}{|\overline{q}-\overline{q}_{obs}|} - \frac{1}{d_0}\right)\left(\frac{\overline{q}-\overline{q}_{obs}}{|\overline{q}-\overline{q}_{obs}|^3}\right)$$
$$= \overline{F}_{rep}(\overline{q})$$

The repulsion force generated by the obstacle $k$

$$\overline{F}_{rep_k}(\overline{q}) = 0 \ if \ \left|\overline{q}-\overline{q}_{obs_k}\right| > d_0$$

the total force exerted on the robot in the position $\overline{q}$ is:

$$\overline{F}(\overline{q}) = \overline{F}_{atr}(\overline{q}) + \sum_{k=1}^{N} \overline{F}_{rep_k}(\overline{q})$$

where $N$ is the number of obstacles in the environment where the robot navigates.

The new position of the robot is given by the following equation:

$$\overline{q}_n = \overline{q}_{n-1} - \delta_i \overline{f}\left(\overline{q}_{n-1}\right)$$

For the potential field approach it is necessary to find the constants that control this behavior, namely $\eta, \varepsilon_1$ and $d_0$.

## 4 DETERMINISTIC FINITE STATE MACHINES

In mobile robots, behaviors are often used for navigation (Arkin, 1998). These methods can be implemented using finite state machines FSM.

Figure 1 shows a simple behavior for a robot whose goal is to avoid obstacles on its path. The robot has two proximity sensors, one on its left ($LS$) and one on its right side ($RS$), allowing it to detect obstacles. The sensors are binary and return 1 when an obstacle is detected within their range. The robot has two motors for propulsion in differential pair configuration.

Figure 1 shows the algorithm state machine (ASM) for the obstacle avoidance behavior shown in the same figure.

There are many ways to physically implement the obstacle avoidance behavior using of state machines. One option is to use standard memories. Figure 2 shows an architecture of a state machine that uses a memory. In it, the ASM is encoded in a look-up table that contains the next state and the outputs of each state. The inputs of the state machine, sensors, and the next state are linked together to form the address of the memory that contains the next state and outputs for the present state.

This type of architecture can be implemented in a FPGA for robots with small computational resources, but also can be implemented using a look-up table in

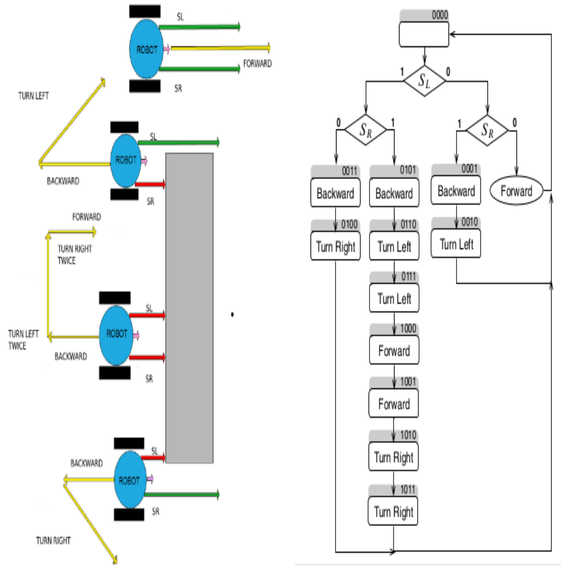



Figure 1: Robot avoiding an obstacle.

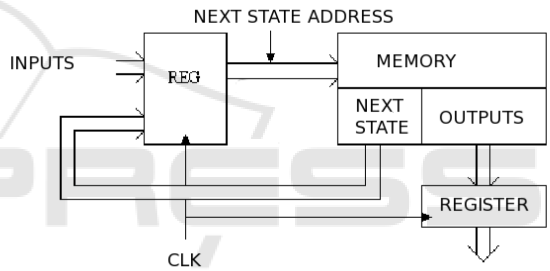



Figure 2: Implementation of an State Machine Using Memories.

high level languages as C/C++, Python, etc. Using this method, depending of the number of states $N_s$, each state is represented by $N_b = \lceil \log_2(N_s) \rceil$ bits. The number of memory locations used is $2^{(N_s+N_i)}$, where $N_i$ is the number of inputs. Figure 1 shows the ASM with 12 states and with two inputs.

Table 1 shows the coding of the actions the mobile robot can perform:

Using this method, each state is represented by $N_b = \lceil \log_2(N_s) \rceil$ bits where $N_s$ is the number of states. The number of memory locations used is $2^{(N_s+N_i)}$, where $N_i$ is the number of inputs.

Table 1 below shows the coding of the actions the mobile robot can perform:

The number of bits to encode the outputs is $N_o = \lceil \log_2(Num.Actions) \rceil$ Thus each memory location requires $N_b + N_o$ bits to indicate the next state and the robot's actions. The obstacle avoidance algorithm shown in Figure 1, requires four memory locations to represent each state, to select the memory location the 4 bits that represent the states and the 2 bits for the

Table 1: Robot Action Coding.

| Robot Action | Binary Code |
|---|---|
| Stop | 000 |
| Forward | 001 |
| Backward | 010 |
| Turn Left (45°) | 011 |
| Turn Right (−45°) | 100 |
| Turn Left (45°) and Forward | 101 |
| Turn Right (45°) and Forward | 110 |
| Turn Right Twice (90°) and Forward | 111 |

inputs are concatenated to form the memory address, then the total number of memory locations necessary is 64, with a width of each location of 7 bits.

For the ASM shown in Figure 1, the state 0 has one conditional output (Forward) shown inside the oval. This output is generated when both inputs *LS* and *RS* are zero. For any the other cases the robot will Stop. The inputs LS and RS represent the digital value from the sensors. Table 2 shows the encoding of this state 0.

Table 2: AFSM MEMORY.

| Pr. State $S_t$ A B C D | Inputs LS RS | Next State $S_{t+1}$ ABCD | Outputs $b_2b_1b_0$ |
|---|---|---|---|
| 0 0 0 0 | 0 0 | 0 0 0 0 | 0 0 1 |
| 0 0 0 0 | 0 1 | 0 0 0 1 | 0 0 0 |
| 0 0 0 0 | 1 0 | 0 0 1 1 | 0 0 0 |
| 0 0 0 0 | 1 1 | 0 1 0 1 | 0 0 0 |

As we can see in Table 2 changing one of the bits of the memory will change the algorithm hance also the robot's behavior. For instance, in the third row of Table 2, if two bits of the memory contents are randomly changed as in Table 3, the state machine will jump to $est_{11}$ instead of state $est_3$ given the same conditions, generating therefore a *Turn Right* output instead of a *Stop* one.

Thus, one of the goals is to find the best configuration of the memory content to get a robot's behavior.

Table 3: Third raw State 0 AFSM MEMORY.

| Pr. State $S_t$ A B C D | Inputs LS RS | Next State $S_{t+1}$ ABCD | Outputs $b_2b_1b_0$ |
|---|---|---|---|
| 0 0 0 0 | 1 0 | 1 0 1 1 | 1 0 0 |

Without or small errors in the sensing and in the movements the robot, under the same conditions, that is, with the same initial pose, $x_o, y_o, \theta_o$ and same destination $x_d, y_d$, the robot should behave always in the same way, because the algorithm that control it it is deterministic. While this type of behavior is desired for some robotics applications, in others it would be desired that the robot behaves in a different way each time under similar conditions, thus a probabilistic FSM is used. This kind of state machines are build using HMM, as it is explained in the next section.

## 5 PROBABILISTIC FINITE STATE MACHINES

The algorithm of a Probabilistic Finite State Machines (PFSM) depends on random variables (Vidal and Thollard, 2005) and therefore it can be model using Hidden Markov Models (HMM). In this section, we explain our approach to this problem, referred as the Behavior HMM, and later it is explained how we optimize this model through Genetic Algorithms (GA).

### 5.1 Hidden Markov Models

A HMM is a doubly stochastic process, in which the set of states $S$ is hidden and the set of symbols $O$ are observable (Rabiner and Juang, 1986). The stochastic process exhibits the Markov property, that is, the probability of reaching a particular next-state depends only on the current state and not in the whole history of the process. States are not directly observable and can only be inferred by their probabilistic emission of observable symbols.

The observation symbols are $V = (V_0, V_1, \ldots, V_L)$. And the probability of emitting symbol $k$ being in state $i$, $b_i(k) = p(O_t = k | S_t = i)$, where $S_t = i$ means the Markov chain was in state $i$ at time $t$, and $O_t = k$ means the observed symbol at time $t$ was $k$.

The transition probability defines the probability of taking the transition from a particular state to another state or itself. Where $a_{ij}$ is the probability of taking a transition from state $i$ to state $j$:

$$a_{ij} = p(S_{t+1} = j | S_t = i).$$

Also included is the initial state distribution probability:

$$\pi_i = P[s_1 = S_i], \qquad 1 <= i <= N$$

A standard Markov model is formed by a structure called $\lambda = (A, B, \pi)$, where A and B are two matrices with components: $A = (a_{ij})$, $B = (b_{ik})$ for all $i, j$ and $k$, with $N$ states and $L$ observation symbols; and $\pi$.

## 5.2 Discrete Hidden Markov Models for Robots Behaviors

In this work, we propose a probabilistic representation of the algorithm's FSM by a HMM, in this, the states are part of a probabilistic state machine, that have the similar characteristics as the states in the deterministic ones, but taking into consideration the stochastic behavior of the system. There is a direct matching between the inputs of the FSM, becoming observations in a HMM, and also for the transitions from one state to another. The inputs in the deterministic FSM become the observation in the HMM. That is, the observation symbols are formed by quantized version of the input sensors as is explained in Section 5.5.

The decision to change to another state depends on the present state $S_t$, the observed symbol $O_t$ at time $t$ and the $\lambda$ model of the HMM.

Given a HHM model $\lambda = (A, B, \pi)$ with $N$ states and $L$ observation symbols, and with the system been in states $\{S_1 ... S_{t-2}, S_{t-1}\}$, past observation sequence $\{O = O_1, O_2, ..., O_{t-1}\}$ and a new observation $O_t$, to find which will be the next state $s_j$ at time $t$, it is necessary to calculate the maximum transition probability of going from any state $i$ to $j$:

$$\delta_t(j) = \max_{1<i<N} P[S_1 \dots S_{t-1} = i, O_1, \dots, O_t | \lambda] \quad (1)$$

where

$$1 < j < N$$

that is, $\delta_t(j)$ keeps the highest probability of reaching state $j$, and this calculation is done with all states $1 < i < N$. This is similar to the calculations used by the Viterbi algorithm (Viterbi, 1967; Rabiner and Juang, 1986) to find the best sequence of states that reaches a particular state, the difference with our approach is that we want to predict which is the most probable next state. Then the most probable next one is:

$$S_t = j = \arg \max_{1<i<N} [\delta_t(i)]$$

This equation can be calculated recursively, with the following procedure:

Initialization:

$$\delta_1(i) = \pi_i b_i(O_1), \qquad 1 < i < N, \quad (2)$$

$$S_1 = j = \arg \max_{1<i<N} [\delta_1(i)] \quad (3)$$

Recursion:

$$\delta_t(j) = \max_{1<i<N} [\delta_{t-1}(i) a_{ij}] b_j(O_t), \quad 1 < j < N \quad (4)$$

$$S_t = j = \arg \max_{1<i<N} [\delta_t(i)] \quad (5)$$

Figure 3 shows each state having a $\delta_{t-1}$ at time $t-1$ and at time $t$, for each state $j$, $\delta_t(j)$ needs to be calculated again, by taking into consideration the transition probabilities $a_{ij}$ and the symbols probabilities $b_j(O_t)$.

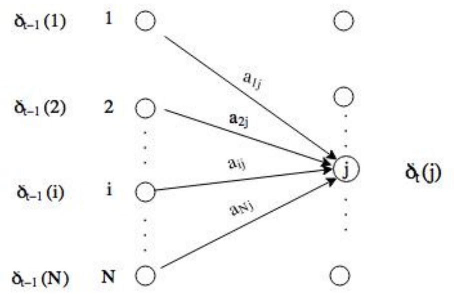



Figure 3: Best next state $j$ given by $\delta_t(j)$.

Thus, matrix B needs to be created taking into consideration equation Equation (4).

## 5.3 Action Symbols

In our approach, we incorporate the outputs of the FSM as action symbols attached to the states of the HMM. The action symbols are:

U = { Stop, Forward, Backward, Turn Left (45°), Turn Right (−45°), Turn Left and Forward, Turn Right and Forward, Turn Right twice (−90°) and Forward} $= \{U_0, U_1, U_2, U_3, U_4, U_5, U_6, U_7\}$.

Figure 4 shows the structure of the HMM taking into consideration the sensor symbols (FSM inputs) and the action symbols (FSM outputs).

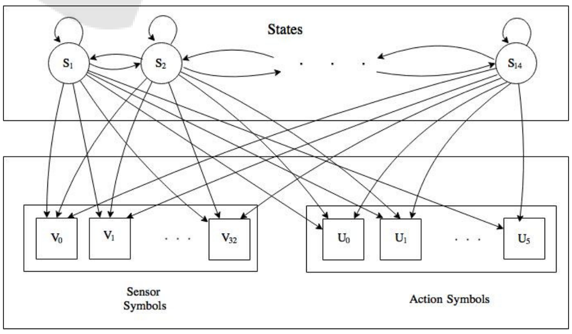



Figure 4: Extended version of an HMM, the sensor inputs and the robot's actions are incorporated in the HMM.

Thus, we needed to incorporate matrix $C$, into the robot's behavior model HMM $\lambda = (A, B, C, \pi)$, that contains the probability of generate an action $AC_t = U_k$ given that we are on state $S_t = j$ and with observation $O_t = Vi$:

Let $C = c_{l,k}$ such as $l = \text{concat}(j,i)$ where *concat* is a bit concatenation operation, $j$ is the index of the state $S_t$ and $i$ is the index of observation $O_t$

$$c_{l,k} = p(U_t = k | S_t = j, O_t = i).$$

To form the $C$ matrix's rows indices is a concatenation of the state's index $j$ together with the observation index $i$.

We call this new type HMM model $\lambda = (A,B,C,\pi)$ an extended HMM (EHMM).

## 5.4 Execution of the Behavior HMM

To start the execution of the probabilistic state machine, given the robot's behavior model EHMM, $\lambda = (A,B,C,\pi)$, first the robot needs to make an observation at time $t = 1$, $O_1$, and then to calculate the following equations to find the first state:

$$\delta_1(i) = \pi_i b_i(O_1), \qquad 1 < i < N, \qquad (6)$$

$$S_1 = j = \arg \max_{1<i<N} [\delta_1(i)] \qquad (7)$$

Once the first state is calculated then the output action needs to be found, due to the stochastic nature of the probabilistic state machine, the output is not just generated using the action symbol with the highest probability in that state, but by generating a random number and comparing in which region it is of all possible outputs in a particular case. In our approach, the row of matrix $C$ to be used in the calculation of the probabilities of the output is by a concatenation of the state's index $j$ together with the observation index $i$. With this row, a range of the outputs symbol probabilities is created, as it is shown in Table 4.

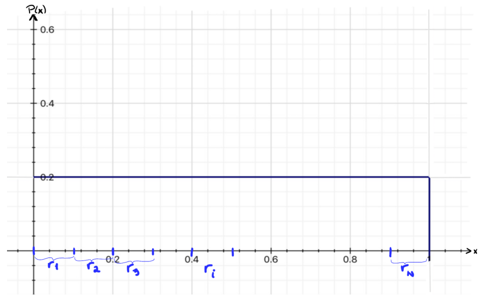
Table 4: Symbol output range table.

| **Output** $i$ | **Range** | $r$ |
|---|---|---|
| 0 | $[0, c_{ji,1})$ | $r_1$ |
| 1 | $[c_{ji,1}, c_{ji,1} + c_{ji,2})$ | $r_2$ |
| ... | ... | ... |
| k | $[\sum_{m=1}^{k-1} c_{ji,m}, \sum_{m=1}^{k} c_{ji,m})$ | $r_i$ |
| ... | ... | ... |
| K-1 | $[\sum_{m=1}^{K-1} c_{ji,m}, 1]$ | $r_K$ |

A random number $x$ with uniform density between 0 and 1 is generated and using Table 4 it is checked in which range this number is, if $r_i \le x < r_{i+1}$ then the first state output is $AC_1 = U_i$.

$if\, 0 \le x < r_1$ the output 0 is generated, that is Stop

$if\, r_k \le x < r_{k+1}$ the output $k$ is generated




This procedure continues for $t > 1$ with:

$$\delta_t(j) = \max_{1<i<N} [\delta_{t-1}(i) a_{ij}] b_j(O_t), \quad 1 < j < N \qquad (8)$$

$$S_t = j = \arg\max_{1<i<N} [\delta_t(i)]$$

And generating $AC_t$ in the same way as it was described before.

Summarizing for execution of robots' behaviors using EHMMs:

INPUTS:

EHMM $\lambda = (A,B,C,\pi)$
Robot's initial pose: $\underline{X}_1 = (x_1, y_1)$
Robot's final pose: $\underline{X}_d = (x_d, y_d)$

OUTPUTS:

Robot's actions: $AC$ = { stop, forward, backward, turn left (45°), turn right (−45°), turn left and go forward, turn right and go forward and turn right twice (−90°) and go forward}

$t = 1$
$O_1$ = quantized sensor data in $\underline{X}_1$
$\delta_1(i) = \pi_i b_i(O_1), \quad 1 < i < N,$
$S_1 = j = \arg\max_{1<i<N} [\delta_1(i)]$
$AC_1 = Action(S_1, C)$
WHILE $\{\underline{X}_t \neq \underline{X}_d\}$
$t = t + 1$
$X_t = Movement(\underline{X}_{t-1}, AC_{t-1})$
$O_t$ = quantized sensor data in $\underline{X}_t$
$\delta_t(j) = \max_{1<i<N} P[S_1 ... S_{t-1} = i, O_1, ..., O_t | \lambda],$
$1 < j < N$
$S_t = j = \arg\max_{1<i<N} [\delta_t(i)]$
$AC_t = Action(S_t, C)$
ENDWHILE

The robot's behavior with a PFSM using a model EHMM $\lambda = (A,B,C,\pi)$ can be optimized by several methods: Waum-Welch, Genetic Algorithms, etc. In our research, we optimized the model using GA.

### 5.5 Range Quantizer

In our research a range vector quantizer is used, which has $N$ range centroids vectors that best represent the majority of the sensor readings. To create the range quantizer first the robot collects range vectors.

$$\underline{S_t} = (r_1^t, r_2^t, \ldots, r_i^t, \ldots, r_M^t)$$

Each $r_i^t$ represents distance from the range sensor to the objects in line of sight at time t.

The robot navigates in the environment to collect range vectors by taking readings with its range sensors:

$$\underline{S_1} = (r_1^1, r_2^1, \ldots, r_i^t, \ldots, r_M^1)$$
$$\underline{S_2} = (r_1^2, r_2^2, \ldots, r_i^t, \ldots, r_M^2)$$
$$\ldots$$
$$\underline{S_J} = (r_1^J, r_2^J, \ldots, r_i^J, \ldots, r_M^J)$$

Given a set of $N_J$ vectors of range readings, a set of centroids $\underline{C} = (\underline{C}_1, \underline{C}_2, \ldots, \underline{C}_N)$ that best represent them, is found using the vector quantization Lloyd's algorithm called LBG (Linde-Buzo-Gray).

The robot gets a reading with the range sensor, obtaining a range vector $\underline{S_t}$ and to quantize it, it is compared with each of the centroids of the range quantizer $\underline{C}$. And it is choose the centroid vector $\underline{C}_i$, that is the closest vector to it.

The centroid $\underline{C}_i$ is chosen if:

$$d(\underline{S_t}, \underline{C_i}) < d(\underline{S_t}, \underline{C_j}) \quad \forall j$$

$$d(\underline{S_t}, \underline{C_t})$$

is a function that measures the similitude of the vectors $\underline{S_t}$ and the $\underline{C}$ vectors of the quantizer.

In this case the similitude function uses the Euclidean distance. For our experiments we use 8 range centroids.

The orientation of the light source relative to the robot is quantized with 8 quadrants.

Also the intensity of the light source is quantized in 4 values.

## 6 EVOLUTIONARY ROBOTICS

Evolutionary Robotics (ER) refers to the field of inquiry comprising methods for automatically generating artificial brains and morphologies for autonomous robots that are inspired by Darwinian evolutionary theory (Floreano et al., 2008). Some applications of ER include (Konig, 2015): (i) obstacle avoidance (Banzhaf et al., 1997; Seok et al., 2000; Nelson et al., 2009), (ii) wall following (Banzhaf et al., 1997), (iii) object seeking (Banzhaf et al., 1997), (iv) active vision (Marocco and Floreano, 2002), and (v) object detection.

Our research is concentrated on how to evolve robots algorithms for object seeking and obstacle avoidance using the concept of deterministic and probabilistic state machines. To achieve this goal FSM and Extended Hidden Markov Models (EHMM) robot's behavior model, $\lambda = (A, B, C, \pi)$, are evolved to find individuals that are able to look for light source beacon while avoiding obstacles using Genetic Algorithms.

A GA performs operations over populations of solutions that resemble sexual reproduction, mutation and artificial selection of apt individuals in a given environment. Often classified within the realm of search and optimization algorithms, it has been argued they are robust techniques that trade off efficacy and efficiency when dealing with different environments by exploiting intrinsic parallelism. The population dynamics allows for the emergent convergence to specific regions of the search space as well as implicit clustering of solutions. Genetic algorithms have been successfully applied to a variety of engineering and scientific problems. In particular to the evolution of robot controllers and behaviors.

1. First a population is generated randomly, with $L$ individuals $B_1, B_2, \ldots, B_L$, in which each individual's chromosome is a string of binary numbers that represents the behaviors $B_i = \{011011...0101\}$.

The string is separated into small segments that represent the parameters that define the behavior, $B_i = \{bh_{i_0}\, bh_{i_1} \ldots bh_{i_j} \ldots bh_{i_k}\}$.

2. Each individual (chromosome) is evaluated giving a fitness value according to the individual's performance. The fitness function evaluates how well the robot's behavior performed his operation, and it takes into consideration several aspects of its performance.

Some of them are: the distance between the last position reached and the goal, the number of times the robot hits an obstacle, the number of steps used to reach the goal and also the number of times the robot went backward, etc.

The Fitness function used in our experiments is:

$$Fitness = K1 * N * D_o + K2 * N / D_d + K3 * S_d$$

The mobile robots have $N_k$ discrete times to go from an origin to a destination. $N_s$ is the number of steps of that the robot used to reach a destination. If the robot did not reach the destination $N_s = N_k$.

For the first term of the *Fitness* function, $N = (N_k - N_s + 1)$

$D_o$ is the distance between the last position of the robot $\underline{X}$ and the robot's original position $\underline{X}_o$: $D_o =$

$\|\underline{X} - \underline{X}_o\|$, that means that a robot that uses few steps to reach the destination and it gets faraway from its original position will be well evaluated.

For the second term $D_d$ is the distance between the last position of the robot and the destination goal, plus distance of to the destination using the shortest path found by the Dijkstra algorithm in a topological map of the environment. This is to make the robot to learn that even that is closed to an obstacle, but if there is an obstacle in front of it, it needs to surround the obstacle. The Dijkstra algorithm is only used for training, when the final behavior is obtained, is no longer used by the robot navigation system.

$$D_d = \|\underline{X} - \underline{X}_d\| + DistDijkstra(\underline{X}, \underline{X}_d)$$

DistDijkstra $(\underline{X}, \underline{X}_d)$ is a function that measures the distance of the nodes of a topological that joins the last position of the robot $\underline{X}$ and the destination position $\underline{X}_d$ using the Dijkstra algorithm. Dividing N by $D_d$ makes this function to reward individuals that get closed to the destination.

The third term of the Fitness function is the standard deviation σ, $S_d$, of the robot's positions $\underline{X}_i$ between the robot's original position $\underline{X}_o$ and its final position $\underline{X}$. This term is to measure if the robot went into a local minimum.

Constants $K_1, K_2$ and $K_3$ are used to tone the performance of the robot according to its specifications. The value of the constants $Ks$ where found empirically: $K_1 = 10$, $K_2 = 20$ and $K_3 = 11$.

3. Select the best individuals according to their fitness function and create a new population with individuals generated trough evolutionary's operators (selection, crossover and mutation).

4. The offspring and their selected parents form the new population.

5. Iteration from 2 to 4 is repeated for $M$ generations or until the overall fitness criteria between two generation is less than a given ε, or total number of generations $N_g$ is achieved.

- Evolving Robot Behaviors using Potential Fields.

For the potential field approach we evolved some of the constants of this behavior: $\eta, \varepsilon_1$ and $d_0$.

Each of these constants where represented by 16 bits, 1 bit for the sign, 7 bits for the integer part and 8 bits for the fraction one. Thus, each individual was represented by 48 bits, and the population consist of 100 individuals. This requires 48 bits per individual's chromosome.

- Evolving FSM Behaviors.

The algorithm of the FSM was implemented using the concept described before of building state machines using memories or look-up tables, as is shown in Figure 2. Each Evolved Finite State Machines (EFSM) had 16 states (4 bits). The inputs of the sensors are structurated in the following way: 16 range values are introduced in a range vector quantizer with eight centroids, with the index of the closest centroid, the quantized quadrant index and the quantized light source, they are concatenated to form the input. This input is concatenated with the next state to form the next state index for the look-up table. Thus this index is formed by concatenating 2 bits of the quantized light source, 3 bits of the quantized orientation, 3 bits of the index of the range VQ and 4 bits that represent the next state, in total giving 12 bits. Then the size of the look-up table is 4096 rows of a size of 7 bits each, 4 bits that represent next state and 3 bits to indicate the output. This requires 28672 bits per individual's chromosome.

- Evolving EHMM Behaviors.

The extended HMM requires to find each of the components of its model $\lambda = (A, B, C, \pi)$. For the EHMM behaviors we defined each individual chromosome as follows: number of states $N_s = 16$, number of observation symbols $N_l = 256$, number of outputs $N_o = 8$, and the number of bits per variable $N_b = 8$.

Then, there are $N_s$ probabilities variables for vector π, $N_sN_s$ for matrix A, $N_sN_l$ for matrix B and $(N_sN_l)N_o$ for matrix C. In total the number of bits per individual is

$$N_t = N_b(N_s + N_sN_s + N_sN_l + N_sN_lN_o).$$

$$N_t = 8x(16 + 16x16 + 16x256 + (16x256)x8) =$$

$$297,088$$

## 7 EXPERIMENTS AND RESULTS

We tested the behaviors using our simulation module, in which range readings to obstacles can be simulated, as well as, the robot's movements. The simulated mobile robot had a 240 degree simulated range readings, as the laser Hokuyo URG_04LXUG01, selecting the readings with a separation of 15 degrees each, making 16 range readings in each sensing.

The destination goal is described by a yellow circle; the free space is green; the obstacles are described by polygons in red; the robot is a black circle and the proximity sensor readings are represented by blue colors.

For the genetic algorithm, we had a population of 100 individuals and the evolution lasted 900 generations. The robot's radio was $r = 3cm$. During the execution of the GA, noise was added to the movements of the robot, as well as, to the sensors: for the linear movement it was added a random variable with a uniform density function of $[-0.004, 0.004]$ meters, for rotation movement a uniform density function of $[-0.03927, 0.03927]$ radians and for the range sensor a Gaussian random variable with mean $\mu = .004$ and standard deviation $\sigma = .0004$. The behaviors, to avoid obstacles, were tested in 13 simulated environments, with different sizes, configurations, robot's starting positions and goal destinations. There were two types of environments: one with random generated polygons; and office type environments, similar to the shown in figures 5 and 6

The Figures 5 and 6 show evolved behaviors with a robot starting in a initial position and reaching a destination, a light source, in two types of environments.

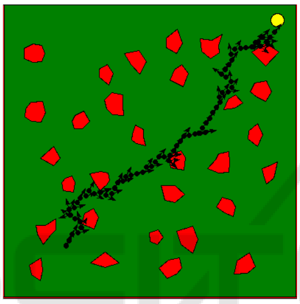


Figure 5: The path found by an evolved robot's behavior in a polygon type environment.

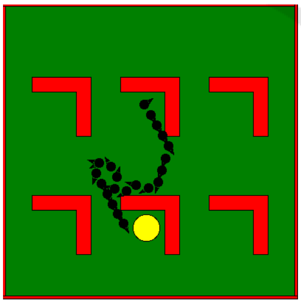


Figure 6: The path found by an evolved robot's behavior in a office type environment.

Table 5 shows the average performance of the best individuals for each of the behaviors in polygon and office type environments, during 1000 trials. As we can see in both cases the best performance is done by the FSM behavior.

Despite the fact that all the behaviors performed worst in the office type environments, we can see that in this type of environments the performance of the behaviors with memory, the FSM and PFSM are much better than the potential field behavior approach, that does not have any memory. In polygonal type environments the FSM is better than the potential field approach by 14.8 % and for office type environments is by 21.94 %.

Table 5: Best average fitness of the behaviors in two different type environments: Polygons and Office.

| | Env. Polygons | Env. Office |
|---|---|---|
| Behavior | Fitness | Fitness |
| FSM | 4267 | 2541 |
| PFSM | 4243 | 2153 |
| POTENTIALS | 3635 | 1983 |

## 8 CONCLUSIONS

We proposed the optimization of the methods for potential fields and state machines to achieve mobile robot behaviors, the state machines were built using deterministic and probabilistic methods. For the deterministic FSM we proposed an architecture of a state machine that uses a look-up table that encodes the algorithm, that is, the robot behavior. This look-up table contains the next state and the outputs of each state. The inputs of the state machine, sensors, and the next state are linked together to form the index of the look-up table that contains the next state and outputs for the present state. For the PFSM a modified version of Hidden Markov Models, that we called EHMM, was used to encode the mobile robot behavior. We also proposed how to find the optimum behaviors for potential field approach, the FSM and the PFSM using Genetic Algorithms. Our experiments proved that the obtained robots' behaviors, when they are used for robot navigation, that the deterministic FSM outperforms the potential field approach and the PFSM.

The robot's behaviors using FSMs and the PFSMs outperforms the ones using potential fields, mainly because they are more complex machines and they are able to stay out of local minima and can retain some memory and learn how to get out of these. Meanwhile the FSM outperforms the PFSMs behaviors due to the type of environments where the experiments were tested and the type of noise that was added to the sensory data, as well as, to the robot's movements. For future work it is necessary to test with more strong noise and more complex HMMs, with more states and observation symbols to see if their performance improves.

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