Proceedings of the 1997 IEEE
International Conference on Robotics and Automation
Albuquerque, New Mexico - April 1997

Evolutionary Action Maps for Navigating a Robot in an Unknown, Multidimensional, Stationary Environment, Part II: Implementation and Results.

By
Ahmad A. Masoud†, Samer A. Masoud‡
†Electrical & Computer Engineering, Royal Military College, Kingston, Ontario, Canada K7K 5L0
E-mail: masoud@host.king.igs.net
‡Mechanical Engineering Department, Jordan University of Science and Technology, Irbid, Jordan

ABSTRACT

Here, the BGM that is suggested in the first part of this paper [1] is used to construct a complete path planner for an agent of arbitrary shape that is operating in a totally unknown, multidimensional, stationary environment. The planner does not require any a priori knowledge about the environment to guarantee that a path to the target will be found. Any a priori information about the environment, regardless of its degree of fragmentation or sparsity, can be integrated into the planning process to accelerate convergence and enhance the quality of the path. Details for constructing the planner along with experiments to demonstrate its capabilities are supplied.

1. INTRODUCTION

To the best of the author's knowledge, the potential field approach is the first ever to be used for describing a motion planning procedure [2]. The approach is rich in techniques for utilizing a potential field to guide an agent along a safe path to its target (for an extensive survey of potential-based techniques that cover methods up till 1994 see masoud [3].) Of particular interest are methods that use the stream lines of a potential surfaces that is a solution to a certain Boundary Value Problem (BVP) [4-14]. These methods can be easily expressed using a PDE-ODE system format; hence they are very suitable for constructing SIMPD machines. Despite their effectiveness and the wide variety of planning situations which they can handle, these techniques remained reliant on the availability of an a priori known, full model of the environment to successfully steer an agent to its target. This has led many to, mistakenly, believe that the above deficiency is inherent in the structure of these methods. This work demonstrates that utilizing these methods in the context of the BGM that is suggested in the first part of this paper easily and effectively remedy this shortcoming. It is shown that placing a Hybrid PDE-ODE planner within the confines of a Hybrid Discrete-Continuous time system eliminate the need of having to a priori know the model of the environment. Instead, a self-referential model of the environment evolves as the agent interact with its surrounding. The model progressively develops so that it capture necessary and sufficient information about the environment for the agent to reach the goal. While the available planning techniques that utilize learning for action selection do guarantee convergence, they do not guarantee success from the first attempt the agent makes to reach its target. It is most likely that the agent has to learn from previous failures. However, the suggested planner does guarantee convergence from the first attempt (First Attempt Completeness (FAC).) Subsequent attempts only results in the planner improving its performance.

This paper is organized as follows, section 2 outlines the construction of a PDE-ODE planner (SIMPD machine), section 3 presents simulations, and conclusions are placed in section 4.

2. THE PLANNER

This section outlines several concepts and tools needed for constructing the planner. The agent is described by the simple differential system

$$\dot{x} = u \; . \qquad (1)$$

Unfortunately, the above system implies the unrealistic assumption that the agent can execute any action instruction (u) that the planner supply. While it is more realistic (and much more complicated) to consider an agent governed by the differential system

$$\dot{x} = f(x,u) \; , \qquad (2)$$

where constraints are placed on the action instructions to make them realizable, the above system is still useful with mechanical agents moving at a low speed.

2.1 Differential Constraints

For the types of agents described above, a scalar potential field (a surface, V) is sufficient to emulate the actions of a dense, micro-agent group (this is not always the case for a general agent [12-14].) Here, two differential surface features may be used for constructing the point vectors needed for describing the actions of the individual micro-agents. Either the slope of V is used to construct the micro-control action

$$u(x)= -\nabla V(x), \qquad (3)$$

or the slope of the curvature of the surface is used:

$$u(x) = -\nabla(\nabla^2 V(x)) \; . \qquad (4)$$

To construct a self-behavior (G-type behavior) that would enable the micro-agent group to constructively interact; therefore, generate an action structure which the operator can successfully use to reach the target, the micro-control at every point in state space is constrained with respect to the other micro-controls that are in its immediate infinitesimal neighborhood. The micro-agents are related to each other using

$$\nabla \cdot u(x) = 0 , \qquad (5)$$

where $\nabla\cdot$ is the divergence operator. This choice guarantee the continuity of motion so that no micro-agent can take the "wrong" action of blocking motion before the operator reach the target. Therefore, the governing relation that is used to condition the differential properties of V so that it can emulate a dense, interacting, micro-agent group is the Laplacian operator

$$\nabla^2 V(x) = 0,$$

or the Bilaplacian operator: (6)

$$\nabla^4 V(x) = 0.$$

2.2 State Constraints :

As was mentioned in the first part of this paper, factoring the environment into the action selection process is carried out using boundary conditions. Whenever, the evolving state of the operator is at a location in the environment (state space) that affects its internal environment in a certain manner, it respond by constraining u at that location to the proper action. This is indirectly accomplished by applying the proper Boundary Conditions (BC) on the potential manifold at the particular location in state space. In this work, the only kind of situations which the operator may encounter are hazardous situations that are to be avoided. In the following several BC's that suit the Laplacian and Bilaplacian operator are briefly stated.

2.2.1 The Dirichlet BC's :

The Boundary Value Problem (BVP) for this case is

solve $\qquad \nabla^2 V(x) = 0 , \qquad (7)$

subject to $\quad V(x) = 1 \,|_{x=\Gamma}$, and $V(T) = 0$,

where Γ is the boundary of the forbidden regions, and T is the target point. Unfortunately, this approach is known to suffer from a quickly vanishing gradient field, even for relatively simple workspaces (Figure-1.)

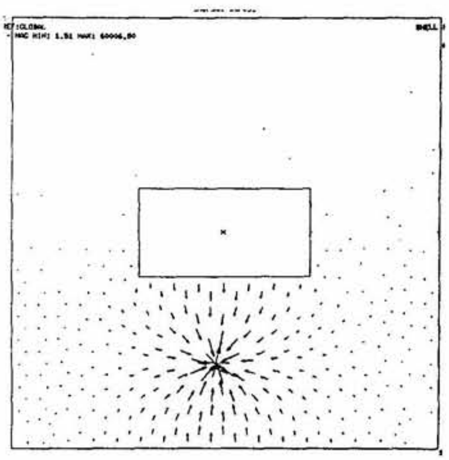


Figure-1: Dirichlet.

2.2.2 The Modified Dirichlet BC's :

To alleviate the vanishing field problem, the following modification is suggested :

solve $\qquad \nabla^2 V(x) = 0 , \qquad (8)$

subject to $\quad V(x) = 1|_{x=\Gamma}$, and $V(x) = 0 \,|_{x=\Gamma_p}$,

where $\Gamma_p = \{x: |x - T| > \rho, \rho>0\}$. As can be seen, the magnitude of the gradient field significantly improved (Figure-2.)

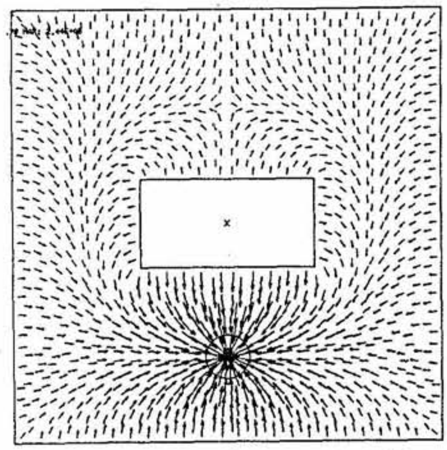


Figure-2: Modified Dirichlet.

2.2.3 The Homogeneous Neumann BC's:

This BVP exhibits remarkable robustness in workspaces with complex geometry :

solve $\qquad \nabla^2 V(x) = 0 , \qquad (9)$

subject to $\quad \dfrac{\partial V(x)}{\partial \mathbf{n}} = 0 \,|_{x=\Gamma}$,

and $\quad V(T) = 0|_{x=\Gamma_p}$, and $V(x_s) = 1$,

where $\mathbf{n}$ is a unit vector normal to Γ, and x_s is the starting point. This approach is effective for point-to-point motion planning. The interest here is in region-to-point planners (Figure-3). Also the paths generated by this technique get dangerously close to the obstacles.

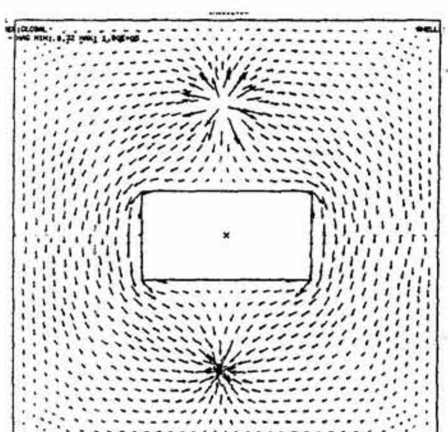


Figure-3: Homogeneous Neumann.

2.2.4 The Nonhomogeneous Neumann BC's:

To remedy the above problem, the following setting is suggested:

solve $\quad \nabla^2 V(x) = 0 \quad ,$ (10)

subject to $\dfrac{\partial V(x)}{\partial n} = C|_{x=\Gamma}$, and $V(x) = 0|_{x=\Gamma_p}$,

where C is a positive constant. In addition to being a region-to-point planner, and providing the path with a good safety margin away from the obstacles (Figure-4), the path has a lower curvature than the above approaches. This is the result of placing no constraints on the direction of the field along the tangent of the obstacles.

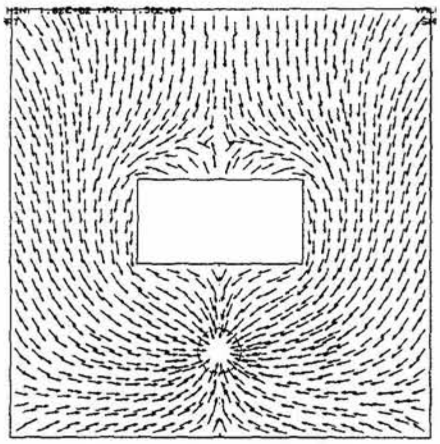


Figure-4: Nonhomogeneous Neumann.

2.2.5 The Biharmonic BC's :

Although the computations here are more expensive, this approach is the most robust in terms of field generation. The generated path is also the lowest in curvature (Figure-5). The BVP is :

jointly solve $\quad \nabla^4 V = 0, \quad$ and

$$(\nabla V)(\nabla V)^t = \lambda[\nabla\cdot\Delta(x,y)]I + G[J(\Delta(x,y)) + J^t(\Delta(x,y))],$$

subject to $\Delta|_{x=\Gamma} \equiv 0,\ \nabla x\Delta|_{x=\Gamma} \equiv 0,$ (11)

and $\quad \sigma_{xx} = P\cdot n_{px},\ \sigma_{yy} = P\cdot n_{py},\ \sigma_{xy} = 0,$

where Δ is a displacement vector, ∇x is the curl operator, λ, P and G are positive constants, I is the identity matrix, J is the Jacobian matrix, n_{px} is the x component of the unit vector that is

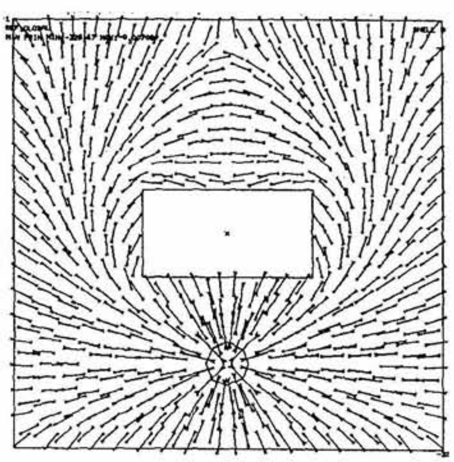


Figure-5: Biharmonic.

normal to Γ_p, n_{py} is the same but for the y component, and

$$\sigma_{xx} = \frac{\partial^2 V(x,y)}{\partial x^2},\ \sigma_{yy} = \frac{\partial^2 V(x,y)}{\partial y^2},\ \sigma_{xy} = \frac{\partial^2 V(x,y)}{\partial x \partial y}\ .$$

2.3. Incorporating Evolutionary Behavior:

The PDE-ODE planners above are reliant on an accurate, a priori known model of the environment in order for them to properly function. This makes these techniques susceptible to the same kind of problems that the traditional AI methods suffer from. In the following a procedure is suggested to remove this dependence.

Let the agent be operating in a workspace (Ω) that is a subset of an N-D space constituting its environment ($\Omega \in R^N$.) Let the hazardous regions in that environment be called O ($O = R^N - \Omega$), Γ be the unknown boundary of that region ($\Gamma = \partial O$, $\Gamma \in R^M$, $M \le N$), and Γ' be the subset of Γ which the agent is initially aware of ($\phi \subseteq \Gamma' \subseteq \Gamma$.) Let the region occupied by the agent at time t be R(x,t) which is a priori known and is initially inside Ω. Let $\gamma(x,t)$ be the boundary of that region ($\gamma(x,t) = \partial R(x,t)$.) Let R_s be the sensed region surrounding R,

$$R_s(x,t) = \{x: |x - \gamma(x,t)| \le \varepsilon,\ x \notin R(x,t)\},$$

and $\gamma_s(x,t) = \partial R_s(x,t),$ (12)

where ε is the range of the sensors, $\varepsilon \ll 1$ (local sensing.) Also let q ($q \in R^K$) be the K-D natural coordinates of the agent, q_s the starting point, q_f the final target point, where for both q_s and q_f, $R(x,t_s)$ and $R(x,t_f) \in \Omega$.

The following algorithm satisfy equation-2 in [1] which is needed for successful navigation:

1- Select one of the PDE-ODE planners in 2.2.
2- convert Γ' from the workspace coordinates in to the natural coordinates of the agent Γ'_n (this step is not needed if $\Gamma' = \phi$.)
3- Set i=0 .
4- Solve the BVP subject to the proper BC's on Γ'_n, q_f, and q_s if applicable.
5- Apply the proper vector differential operator to generate the dynamical system

$$\dot{q} = u_i(q, q_f, \Gamma'_n)\ , \qquad (13)$$

and $u_i = \begin{cases} -\nabla V_i(q, q_f, \Gamma'_n) & \text{for the Laplacian.} \\ -\nabla\nabla^2 V_i(q, q_f, \Gamma'_n) & \text{for the BiLaplacian.} \end{cases}$

6- As long as Q=0, generate a path for the agent in its natural coordinates using

$$q(t) = q_s + \int_{to}^{t} u_i(q, q_f, \Gamma'_n)dt\ . \qquad (14)$$

7- If $q(t) = q_f$, halt.
8- If at any instant t_i, Q changes states from $0 \rightarrow 1$ (i.e. the sensors has detected the presence of a hazardous region that was not previously known to the agent (Γ_s),

$$\Gamma_s = R_s \cap \Gamma \not\equiv \phi, \text{ and } \Gamma_s \not\subset \Gamma'_n), \qquad (15)$$

   a. Halt motion (i.e. set $q(t) = q(t_i^-)$.)
   b. Add the point in the natural coordinates of the agent to the known-obstacle contours,

$$\Gamma'_n = \Gamma'_n \cup q(t_i). \qquad (16)$$

9- i = i + 1 ,
10- Go to step 4.

3. RESULTS

Because of limitation on space, simulation is only carried out for the PDE-ODE planner in 2.2.2.

The hierarchical, symbolic, geometric approach to reasoning and planning is a long standing, deeply ingrained tradition. Probably the most influential statement in support of such an approach is that of Galileo Galilei's "Philosophy in written in this great book, by which I mean the universe which stands always open to our view, but it can not be understood unless one first learn how to comprehend the language and interpret the symbols in which it is written, and its symbols are triangles, circles, and other geometric figures, without which it is not humanly possible to comprehend even one word of it; without those one wonders in a dark labyrinth" (1623). The following example demonstrates that an agent can effectively navigate a dark labyrinth without the use of geometrical, symbolic, hierarchical reasoning. Figure-6 shows a point agent attempting to reach a target in a maze; the maze is initially unknown. The agent is restricted to using only local sensing. Figure-6.1.1 shows the agent's trajectory. As can be seen, despite the total lack of knowledge about its environment, and the local nature of its sensors, the agent manage to reach its target. In the process of reaching its target the agent had to adjust its belief (u_i) 45 times (Figure-6.1.(2-5).) Figure-6.2.1 show the trajectory of the agent the second attempt it makes to reach its target. Using the experience acquired from its first attempt the agent managed to eliminate the unnecessary detours from its path. Figure-6.2.(2-5) shows the agent's belief at different stages of evolution during the second attempt. The agent performed 12 adjustments to its belief field. Figure-6.3 shows the third attempt the agent makes to reach its target. As can be seen a smooth, steady, optimum path to the target was achieved without the agent having to make any adjustment to the last belief it acquired from the second attempt. One important result this example reveals is that as far as reasoning and planning are concerned, geometry (or in a more general sense FORM) is not an "a priori" phenomenon that has to precede reasoning. It is, instead, a postriori phenomenon that results from the activates of a more fundamental processes. The example also supports the argument that representations have the soft nature of patterns not the hard ones of rigidly defined icons. As can be seen the final belief of the agent missed part of the environment. Never-the-less the agent managed to construct a well-behaved, optimal path to the target. This result supports the argument made in the first part of this paper, that the value of a representation does not lie in how well it represents its environment, but rather in how well it serves the purpose of the agent.

The second example demonstrates the self-referential nature of planning. A fixed-base, 2-D robotics arm manipulator (Figure-7) is required to flex in a confined environment (move from the initial configuration $(\theta_1=60^{\circ},\theta_2=120^{\circ})$ to the final configuration $(\theta_1=90^{\circ},\theta_2=0^{\circ})$.) Figure-7.1 show the trajectory of the agent and Figure-7.(2-5) show the belief of the agent which had to be adjusted 17 times. As can be seen with no a priori knowledge, the agent managed to reach its target.

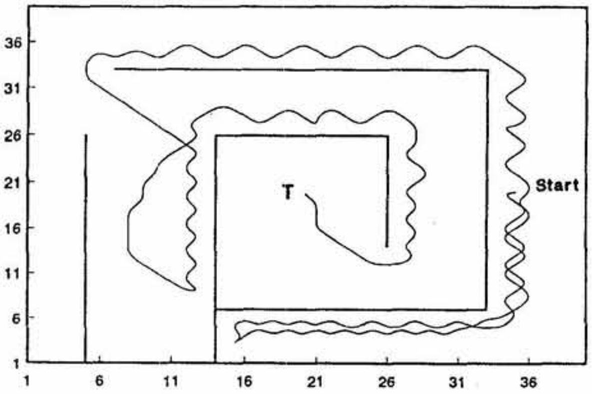


Figure-6.1.1: Point robot, 1'st attempt.

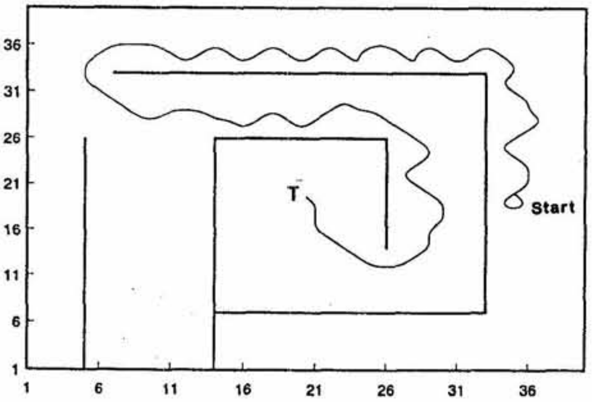
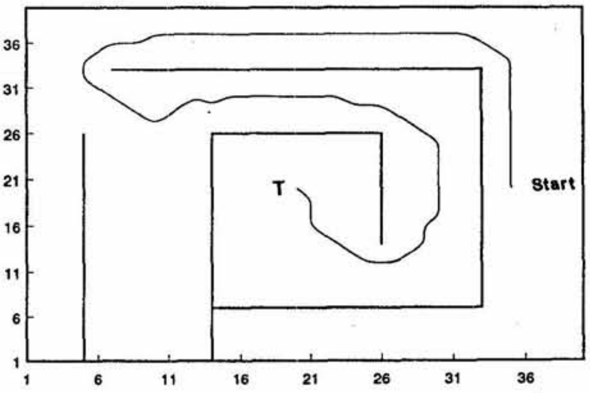


Figure-6.2.1: Point robot, 2nd attempt.



Fiugre-6.3 : Point Robot, 3rd attempt.

The self-referential nature of the planner made it possible to evolve a representation that is matched to the agent. While the resulting pattern may be perceived by an external observer as meaningless irregularity in the vector field substrate, to the agent, these irregularities are a meaningful representation of the environment. In Figure-8 the completeness of the planer is demonstrated. Completeness requires the planner to find a solution if one exist. If no solution exist the planer should halt operation and provide an indicator that a solution does not exist. Here, the planner provide such an indication by degenerating the action field in all the region which the target can't be reached from. In Figure-

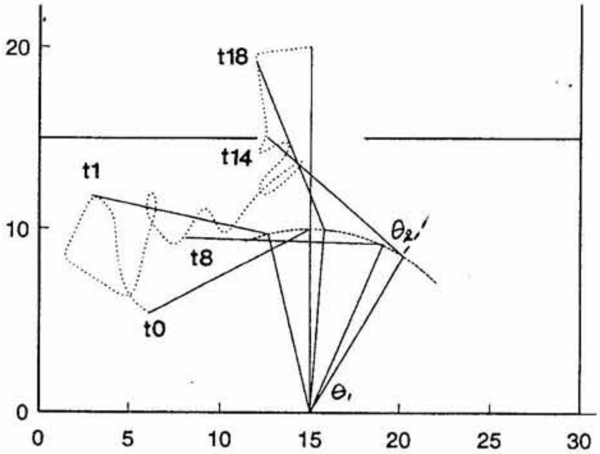


Figure-7.1: Arm manipulator, 1st attempt.

8 the target is placed in a region where it can not be reached from the initial starting point of the agent. Not knowing that the target can't be reached, the agent proceed to the goal adjusting its belief each time an obstacle is encountered. Once the agent reaches the belief that the target is inaccessible, it halts operation and degenerate the field in the region where the target can't be reached from. The agent had to perform 18 adjustments to its belief before making the decision that no path to the target exist.

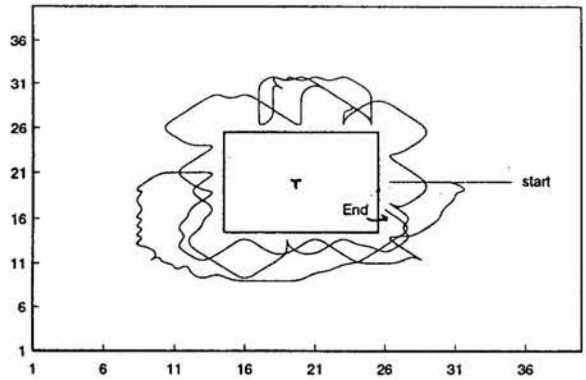


Figure-8.1: Unattainable goal, Point robot.

4. CONCLUSIONS

In this work a complete path planner is suggested for an agent with generic geometry that is operating in an unknown, M-D environment. The work demonstrates the importance of the guidelines suggested by brooks [15] for the construction of intelligent structures that can successfully be imbedded in physical reality. It also uses a multi-disciplinary approach for realizing such a structure. The work contradicts the popular belief that planning in a high-dimensional environment requires global sensing. It is shown here that the range of the sensors by no means affects the ability of the planner to converge to the goal and that the range is only a factor that controls the rate of convergence. One important property of the planner that was not discussed in this work is the ability of the suggested single-agent planner to be integrated in a multi-agent planning environment [16,17]. This is crucial since any practical application requires the planner to share its workspace with other agents. An antisocial, single agent planner will definitely fail in a multi-agent environment causing conflicts with others and deadlock situations that could paralyze part if not all of the group.

Although the model of the agent that is used here is simplistic, on going work is tackling more realistic models. In [12-14] a PDE-ODE planner is constructed for a realistic robotics arm manipulator. The author is optimistic that the framework suggested in this two-part paper is a first step in a promising approach to intelligent behavior generation in general and motion planing in particular.

REFERENCES

[1] Masoud A.,"Evolutionary Action Maps for Navigating a Robot in an Unknown, Multidimensional, Stationary Environment, Part I: The Navigator's Structure",

[2] Hull C.,"The Goal-Gradient Hypothesis Appllied to Some "Field-Force" Problems in the Behavior of Young Children",The Psychological Review, Vol. 45, No. 4,July 1938, pp.271-299.

[3] Masoud A.,"Techniques in Potential-based Path Planning" Ph.D. Thesis, Elec. & Comp. Eng. Dept., Queen's Univ., Kingston, Ontario, Canada, March 1995.

[4] Satoh K.,"Collision Avoidance in Multidimensional Space using Laplace Potential", Preprint of 5th Annual Conf. of Rob. Society of Japan, 1987, pp. 155-156, (in Japanese).

[5] Connolly C., Weiss R., Burns J.,"Path Planning using Laplace's Equation", 1990 IEEE Int. Conf. on Rob.& Aut., May 13-18, Cincinnati, Ohio, pp. 2102- 2106.

[6] Keymeulen D., Decuyper J.,"The Fluid Dynamics Applied to Mobile Robot Motion: The Stream Field Method", Proceedings of the IEEE Int. Conf. on Rob. & Aut., San Diego California, May 8-13, 1994, pp. 378-385 .

[7] Connolly C., Grupen R.,"Harmonic Control", Proc. of the 1992 IEEE Int. Symp. on Intel. Cont., 11-13 August 1992, Glasgow-Scotland UK, pp. 503-506.

[8] Tarassenko L., Blake A., "Analog Computation of Collision-free Paths",1991 IEEE Int. Conf. on Rob. & Aut., April 9-11, Sacramento, California, pp. 540-545.

[9] Schmidt G., Azarm K.,"Mobile Robot Navigation in a Dynamic World Using Unsteady Diffusion Equation Strategy", the IEEE/RSJ Int. Conf. on Intell. Rob. & Sys., Raleigh-NC, 7-10 July 1992, pp. 642- 647.

[10] Masoud A., "A Boundary Value Problem Formula tion of Pursuit-Evasion in a Stationary Environment: A Potential Field Approach", the 1995 IEEE Int. Conf. on Rob. & Aut., May 21-27, Nagoya, Japan, pp. 2734-2739.

[11] Masoud A., Masoud S., et. al., "Robot Navigation Using a Pressure Generated Mechanical Stress Field, The Biharmonic Potential Approach", The 1994 IEEE Int. Conf. on Rob. & Aut., May 8-13, San Diego, California, pp. 124-129.

[12] Masoud A., et. al.,"Constraining the Motion of a Robot Manipulator Using the Vector Potential Approach", 1993 IEEE Regional Conf. on Aerospace Control Systems, Westlake Village,

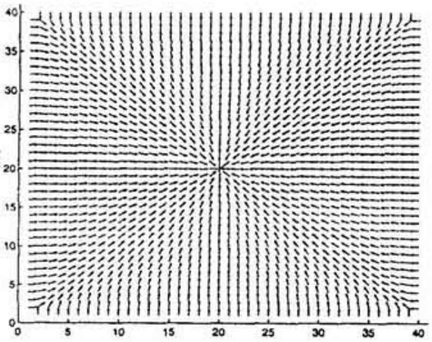


Figure-6.1.2: Belief field, t0.

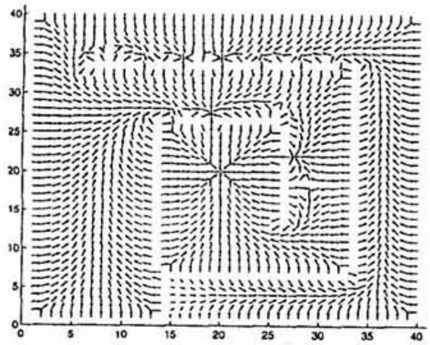


Figure-6.2.2: Belief field, t3.

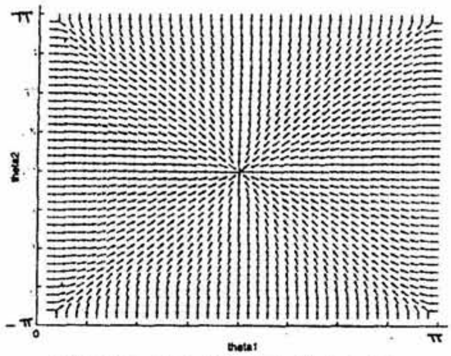


Figure-7.2: Belief field, t0.

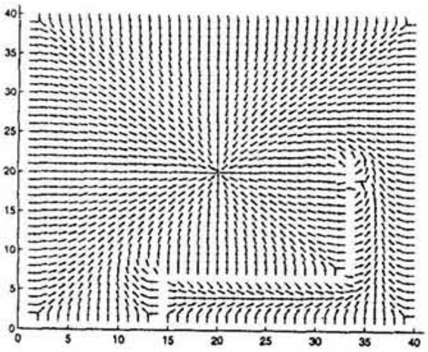


Figure-6.1.3: Belief field, t18.

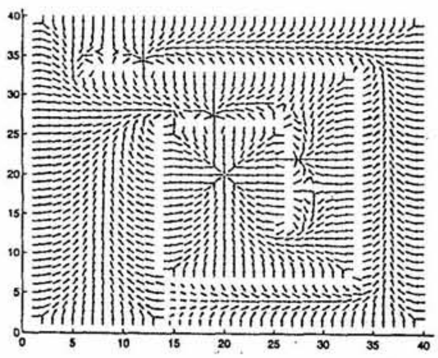


Figure-6.2.3: Belief field, t8.

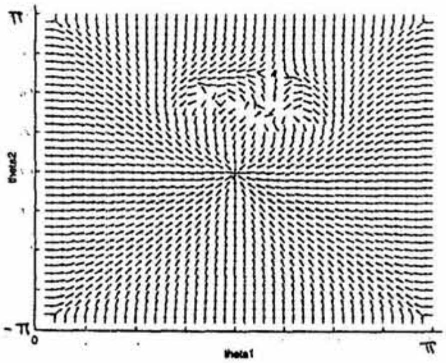


Figure-7.3: Belief field, t8.

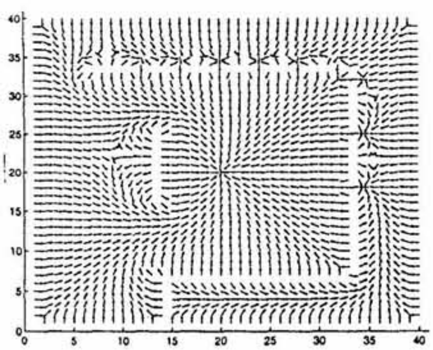


Figure-6.1.4: Belief field, t32.

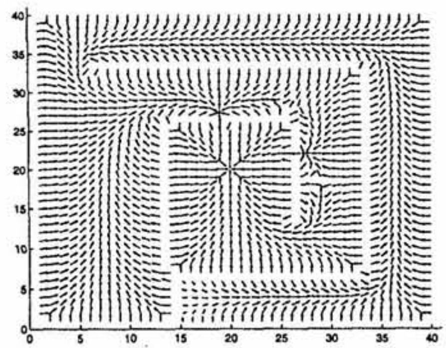


Figure-6.2.4: Belief field, t10.

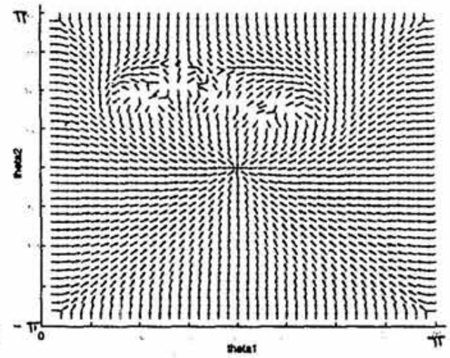


Figure-7.4: Belief field, t14.

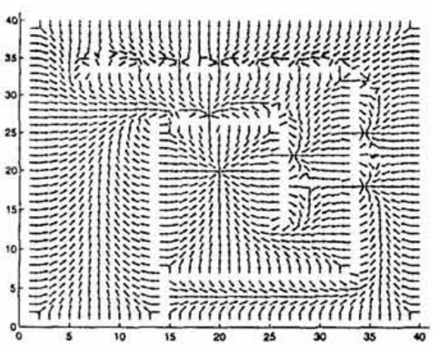


Figure-6.1.5: Belief field, t45.

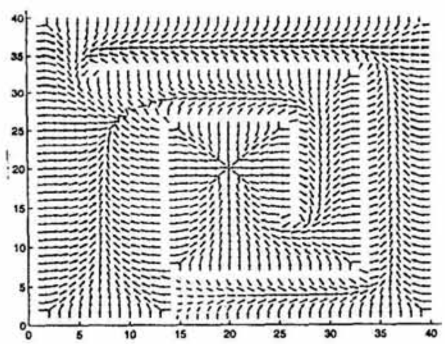


Figure-6.2.5: Belief field, t12.

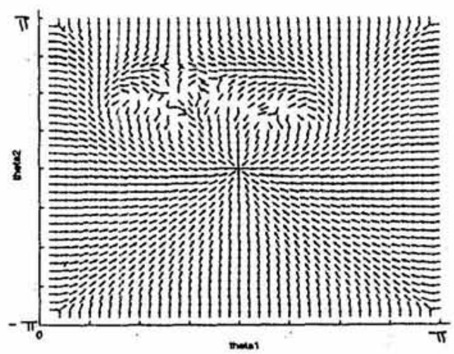


Figure-7.5: Belief field, t18.

CA, May 25-27, 1993, pp. 493-497.

[13] Masoud A., et. al. ," Robot Navigation Using the Vector Potential Approach",1993 IEEE Int. Conf. on Rob. & Aut., Atlanta, Georgia, May 2-7, 1993. pp. 1-(805-811).

[14] Masoud A., "Robot Navigation Using the Vector Potential Approach", submitted to the IEEE Trans. on Systems, Man, and Cybernetics.

[15] Brooks R.,"Intelligence Without Reason", MIT AI Lab., A.I. Memo No. 1293, April 1991.

[16] Masoud A., "A Decentralized, Evolutionary, Hybrid Controller for Directing Traffic Along Two-way Streets", The 35th IEEE Conf. on Decision and Control, Japan, Dec. 11-13 1996.

[17] Masoud A., " Using Hybrid Vector-Harmonic Potential Fields for Multi-robot, Multi-target Navigation in a Stationary Environment 1996 IEEE Int. Conf. on Rob. & Aut., April 22-28, 1996, Minneapolis, pp. 4564-71.

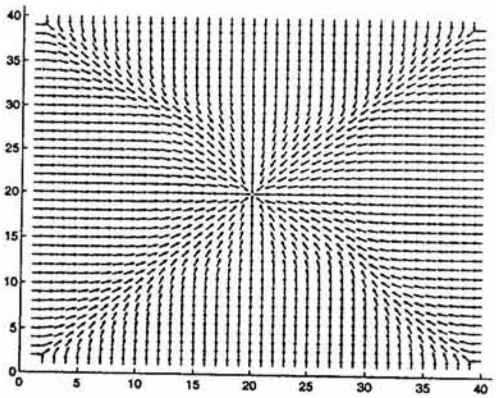


Figure-8.2: Belief field, t0.

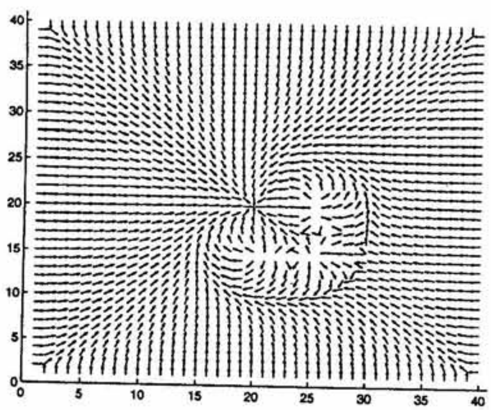


Figure-8.3: Belief field, t4.

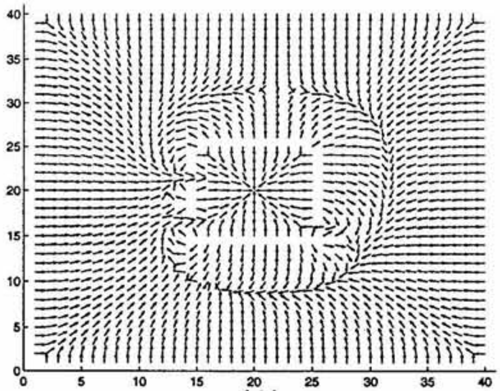


Figure-8.4: Belief field, t15.

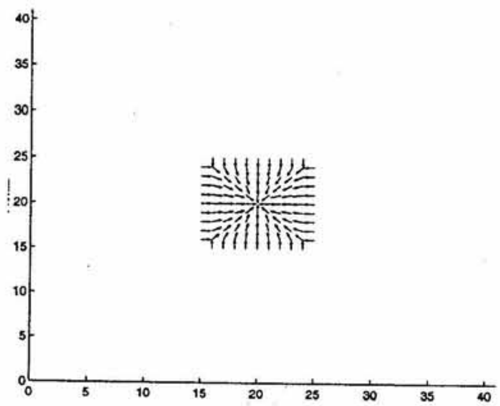


Figure-8.5: Belief field, t18.