A Solids Mechanics-Inspired, Sensor-based Motion Planner

by
Samer M. Charifa *, Ahmad A. Masoud**
* Mechanical Engineering Department, KFUPM, P.O. Box 1131, Dhaharan 31261, Saudi Arabia, msharifa@kfupm.edu.sa
** Electrical Engineering Department, KFUPM, P.O. Box 287, Dhaharan 31261, Saudi Arabia, masoud@kfupm.edu.sa

Abstract

In this paper a motion planner capable of laying a trajectory for a robot operating in a complex, stationary, unknown environment based on the sensory data it acquires on-line from its finite range sensors is suggested. The planner utilizes concepts from the area of mechanics of solids to generate the navigation field. A new setting for the bi-harmonic potential field approach to planning [1] is suggested. The new setting makes it possible to gradually feed the parts of the environment, as they are discovered on-line by the sensors of the robot, to the bi-harmonic potential-based planner. Theoretical development of the method as well as simulation results are provided.

1. Introduction

A motion planner may be defined as a goal-oriented, context-sensitive, constrained, intelligent controller whose job is to instruct a robot on how to direct its motion so that a goal is achieved. Planning has been the center of attention of researchers in robotics and AI. To address the requirements a planner has to meet in order to have a reasonable chance of success when operating in a realistic environment, many methods, approaches, and ways of thinking were and are still being suggested [2,3,4,11]. One promising approach to planning employs boundary value problems (BVP) to properly combine the data about the environment, the goal, and the constraints on behavior to generate a potential field that is in turn used to induce the vector field steering motion of the robot. To the best of our knowledge, the approach appeared in the late eighties through the work of sato on harmonic potential fields [5,6]. An extensive survey of this approach and the potential field approach in general may be found in [7] and [8] respectively. The harmonic potential field approach is the most widely known approach of this type; however, other approaches that use different boundary value problems do exist. One of these approaches is the bi-harmonic potential field approach suggested in [1]. Although the approach is more computationally involved, it offers several advantages over the harmonic approach:

1- the navigation field from a bi-harmonic potential exhibit high numerical stability allowing it to manage environments that are geometrically complex,

2- the curvatures of the generated paths are low and exhibit little fluctuation while maintaining a short path length.

3- unlike many planners who are only capable of point-to-point navigation, the planning action generated by such planners is a region to point action. This is an important feature to have if the navigation template is to be used by other robots situated at different places in the environment.

The bi-harmonic method in [1] can only generate the navigation field for fully known environments. In a realistic situation it is unlikely that such a requirement be accommodated. A sensor-based approach that would gradually feed the content of the environment to the planner is more suitable for real-life operation. In this paper a new setting for the bi-harmonic method that is suitable for use as a sensor-based planner is suggested. The new setting jointly takes into consideration the nature of both the BVP generating the field and the database used by the robot to store the fragments of data acquired about its environment.

This paper is organized as follow: in section 2 a brief background is provided on planners utilizing boundary value problems for generating navigation fields. In section 3 the bi-harmonic approach in a modified setting is discussed. Simulation results are reported in section 4 and conclusions are placed in section 5.

2. Background

A properly constructed BVP is the core of a special type of motion planners called: evolutionary, hybrid, PDE-ODE controllers (EHPC), An EHPC (figure-1) consists of two parts:

1- a discrete time-continuous time system to couple the discrete-in-nature data acquisition process to the continuous-in-nature action release process;

2- a hybrid, PDE-ODE controller (HPC) to convert the acquired data into in-formation that is encoded in the structure of the micro-control action group out of which a control action is selected to steer motion.

In general, the control signal provided by an EHPC should simultaneously provide guidance for a robot and manage its dynamics. Ongoing work aims at providing EHPCs with such a capability [7]. The version considered here can only provide a guidance signal in the form:

$$\mathbf{u} = -\nabla V(x, \beta, S(t_n), \Gamma_o(t_n)) \tag{1}$$

so that for the gradient dynamical system:

$$\dot{x} = -\nabla V(x, \beta, S(t_n), \Gamma_o(t_n)) \ , \qquad (2)$$

$$\lim_{\substack{n \to Z \\ t \to \infty}} x(t) \in \beta$$

and: $$x \cap O \equiv \phi \qquad \forall t,$$

where V is a potential field, n represents the n'th instant at which the robot's sensors pick up a novel event in the form of new data about the environment (t_n) , Z is a finite, positive integer, ∇ is the gradient operator, and β is the target zone. $S(t_n)$ is a binary variable with ground state 0. It changes state from 0 to 1 at t_n. It is then set back to 0 when the newly discovered information, $\Gamma_o(t_n)$, is added to the evolving database of the robot represented by the set Γ and the control field is adjusted accordingly.

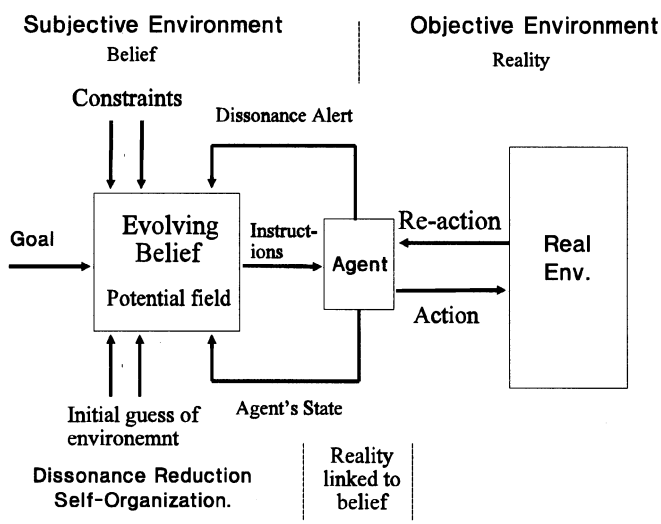

Figure-1: An evolutionary structure for motion planners.

The potential field V is generated using a suitable BVP. Below is one of the BVPs utilized by the harmonic potential field approach

$$\nabla^2 V(x) \equiv 0 \qquad x \in R^N - \Gamma - \beta$$

subject to: $$V = 0|_{X=\beta} \ \& \ V = 1|_{X \in \Gamma} \ . \qquad (3)$$

The BVP for generating the bi-harmonic navigation field suggested in [1] is:

$$\nabla^4 V(x, y) \equiv 0 \qquad x,y \in \Omega$$

and

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

subject to:

$$\frac{\partial^2 V(x, y)}{\partial x^2}|_\beta = P \cdot n\beta_x, \frac{\partial^2 V(x, y)}{\partial y^2}|_\beta = P \cdot n\beta_y, \frac{\partial^2 V(x, y)}{\partial x \partial y}|_\beta = 0.$$

and

$$Q \equiv 0, \qquad \nabla \times Q \equiv 0 \qquad x, y \in \Gamma \qquad (4)$$

where V is a scalar potential field, Ω is the work space of the robot, Γ is the boundary of the obstacles, I is the identity matrix, J is the jacobian matrix, $n\beta_x$, $n\beta_y$ are the x and y components of the unit vector normal to β where β is the region surrounding the target zone, λ and G are positive constants. $Q = [u \ v]^t$ is the displacement field, where u is its x component and v is its y component. The lines of the minimum principal stress are traversed in order to guide motion to the target along an obstacle-free path. A sample of the steering field generated by the bi-harmonic approach is shown in figure-2.

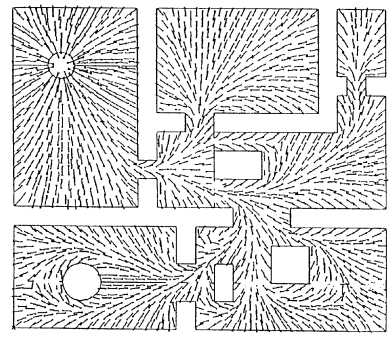

Figure-2: Navigation field from a bi-harmonic potential .

3. The planner

In this section the suggested sensor-based planner is described.

The building blocks:

Special care has to be taken when the environment of the robot, represented by Γ, is not readily available. One of the issues that needs to be considered is the compatibility of the, most probably, noisy fragments of data about the environment of the robot which is being acquired by the sensors of the robot at discrete instants in time ($\Gamma_o(t_n)$) with the BVP synthesizing the navigation field. The physical nature of a BVP describing mechanics of material fields does not admit all types of geometries. For example, isolated points of the boundary or segments exhibiting high level of discontinuities may cause the solution of the BVP to degenerate. Another important issue is the fact that the discrete-in-time stream of fragmented boundary contours must have a form suitable for storage in a database which the utilizing mobile robot can use to construct an evolving representation of its environment. A third important consideration has to do with the algorithms and software needed to solve for the stress field. As can be seen, the BVP for the bi-harmonic potential has a more involved form than its harmonic counterpart. This, on its own, may make the harmonic potential approach more desirable than the bi-harmonic approach. It is important that whatever method used for feeding back the content of the environment to the planner be compatible with an accessible, off-the-shelf BVP numerical package (e.g. the Matlab PDE toolbox).

These authors believe that the database suggested by Moravec [9] for logging the sensory data acquired online by a mobile robot meets all the above requirements. The database uses circles as the building blocks of representation. Any fragments of data collected by the robot is made to fit into a

circle. The radius and center of the circle are then logged in a table format (Figuer-3). The smooth well-behaved boundary of a circle guarantees a trouble-free generation of the bi-harmonic navigation field. Moreover, the Matlab PDE toolbox [10] has the ability to automatically accommodate the presence of a circular boundary in a BVP by simply providing both the location of its center and its radius.

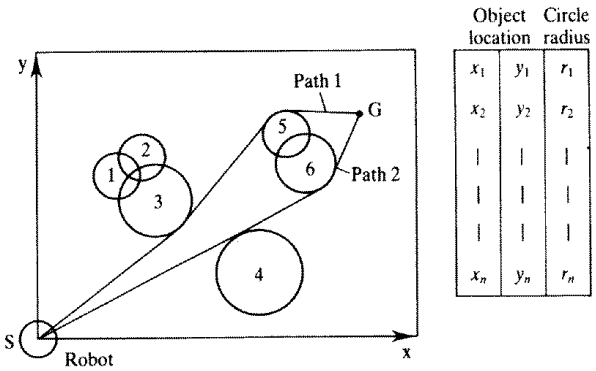

Figure-3: circles as building blocks of representations.

The circular building primitives have the form:

$$\Gamma_o(x, y, x_i, y_i, r) = \{x, y : [(x - x_i)^2 + (y - y_i)^2]^{1/2} = r\} \quad (5)$$

The generative BVP:

The BVP used to generate the steering field is similar to the one in (4); however, the boundary conditions are set differently,

$$\nabla^4 V(x, y) \equiv 0 \qquad x,y \in \Omega$$

and

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

subject to:

$$Q = -c\,\vec{n}\Big|_{\Gamma} \quad \text{and} \quad Q = c\,\vec{n}\Big|_{\beta} \qquad (6)$$

where C is a positive constant and $\vec{n}$ is a surface normal unit vector. The vector at a point P used to steer motion toward the target is:

$$F(P) = \frac{\alpha}{\sqrt{u(P)^2 + v(P)^2}} \begin{bmatrix} u(P) \\ v(P) \end{bmatrix} \qquad (7)$$

where α is a positive constant.

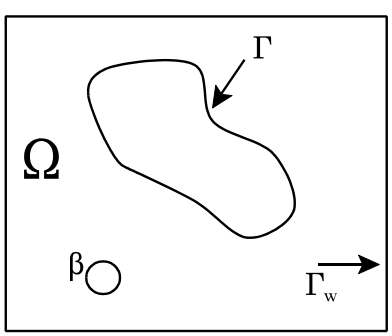

Figure-4: Geometry of the environment

The algorithm:

Figure-5 below shows the flowchart used to implement the sensor-based navigator. The core of the algorithm is a BVP solved numerically by the finite element method (FEM). Since FEM can only handle finite domains, the exterior boundaries of the environment (Γ_w) are assumed to be *a priori* known and are used to initialize the obstacle set, Γ, in the algorithm.

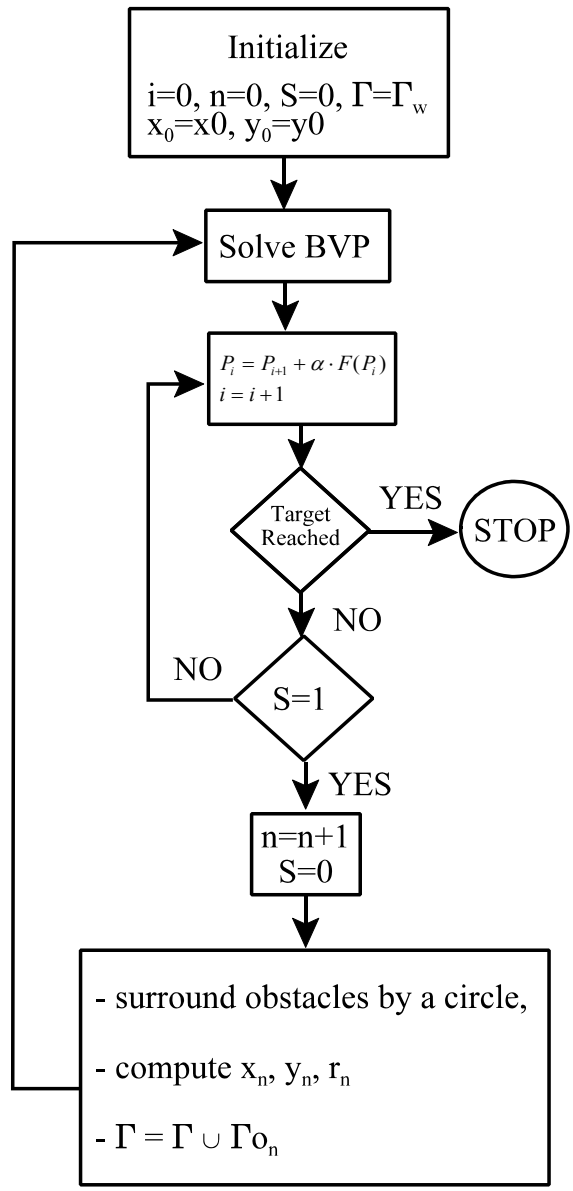

Figure-5: Flow chart of the navigation algorithm.

4. Results

In this section simulation is used to test the capabilities of the planner. The environment the planner is presented with is a simple 12×12 room separated into two parts by a divider that has an opening. The planner is required to move a point object from one part of the room to the other. The sensor used here is a local, narrow beam range sensor that can detect objects within a circular region of radius 1.2. The radius of the circular building blocks is 0.15. The starting point of motion is: x=3, y=11, and the target point is: x=3, y=1.

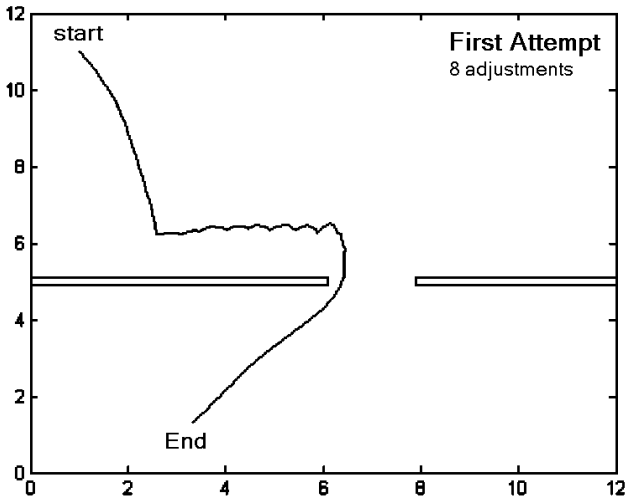

Figure-6: Trajectory, first attempt.

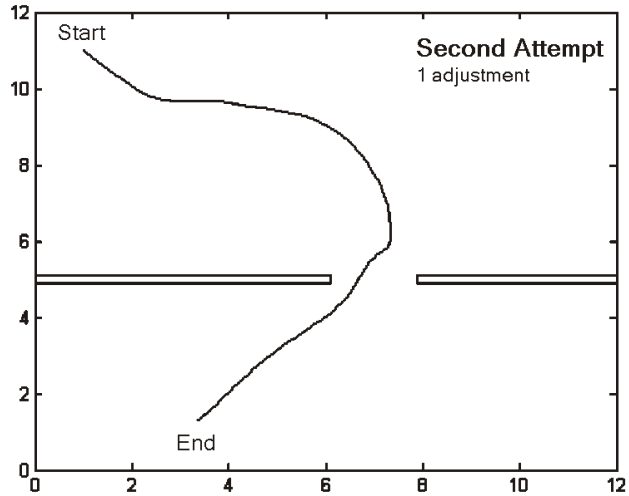

Figure-8: Trajectory, second attempt.

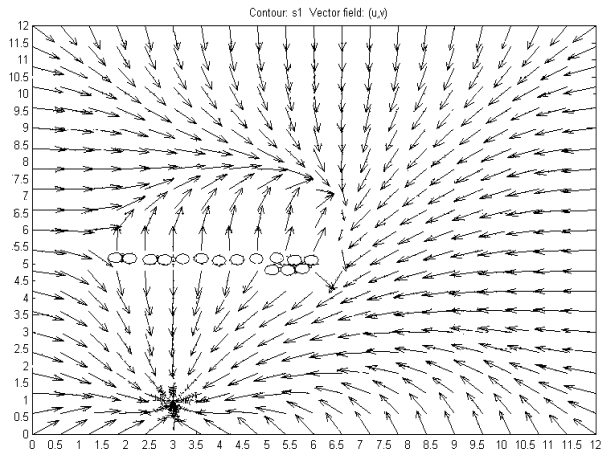

Figure-7: Steering field, first attempt

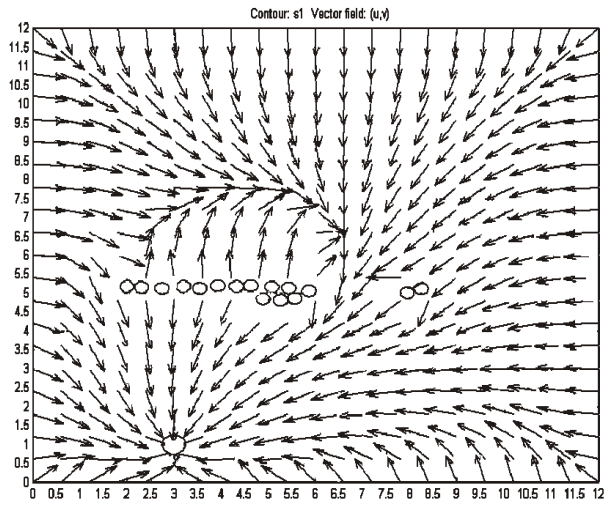

Figure-9: Steering field, second attempt

The planner starts steering motion not knowing what the contents of the environment are. All what it knows is its destination and the exterior boundaries of the room. As can be seen from figure-6, the planner manages to lay a trajectory to the target that avoids the obstacles relying only on the data its sensors provide. For this case, the sensors of the planner detected the presence of obstacles eight times. Each time it had to adjust the steering field so that the presence of the newly acquired data is accommodated. The navigation field corresponding to the first attempt is shown in figure-7.

Equipped with the knowledge it gained from its first engagement of the environment, the planner tries a second time to reach its target from the same start point. As can be seen from figure-8, the planner was able again to reach its target making use of the experience it accumulated from the previous attempt. This experience was reflected in reducing the computational burden required for the adjustment of the steering field. Also the quality of the path was significantly improved. The sensors picked the presence of obstacles along the trajectory on which motion is heading and adjusted the steering field and the heading only once. The navigation field corresponding to the second attempt is shown in figure-9.

A third attempt by the planner to reach its target from the same starting point yielded no new sensory data or field adjustment. This is an indication that the planner has acquired a necessary and sufficient level of environmental data to lay a conflict-free trajectory to the target. Although the generated path was encoded using a necessary and sufficient level of information, its characteristics both differential and integral are acceptable; actually the quality is very close to that of a path obtained under full *a priori* information. Figure10 shows the trajectory generated during the third attempt.

5. Conclusions

In this paper the bi-harmonic potential field approach to planning is modified to operate in a sensor-based manner that would allow it to plan motion in a unknown environment. The reported method is a part of ongoing work to build a new class of intelligent motion controllers that have a good chance of meeting the demands a realistic environment may present an agent with. The behavior of agents equipped with such controllers is goal-oriented, context-sensitive (i.e. meaningfully react to the events happening in their external environment), and intelligent. Future work on the bi-

harmonic approach will focus on adding more capabilities to this method such as directional sensitivity.

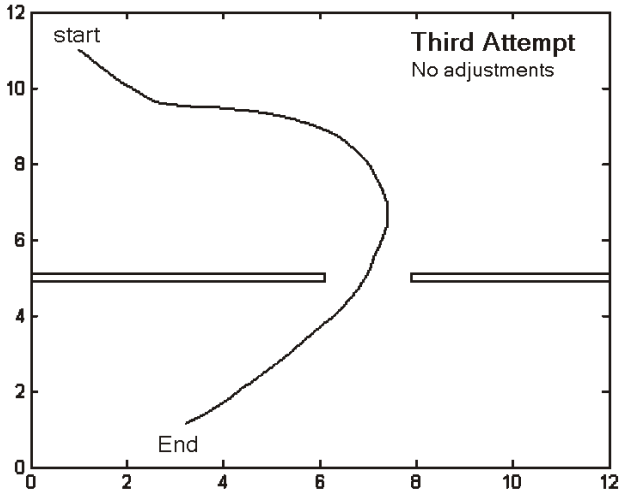

Figure-10: Trajectory, third attempt.

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