IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Arm Motion Planning of Humanoid Robots

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Abstract

The research is conducted to obtain motion planning algorithm of humanoid robots. Our aim is to create the motion of the arm of humanoid robot automatically so that it can avoid obstacles in its surroundings. Our system will use stereo vision to obtain the map of the environment and using mesh modeling, the accumulation of vision input continuously will be done. We will implement PRM (Probabilistic Roadmap) to plan the motion of the robot arm.

Introduction

The arm motion planning of humanoid robots involves the process of determining the appropriate trajectories and configurations for the robot's arm to perform desired tasks. This task requires precise consideration of various factors like robot kinematics, workspace constraints and optimization of motion efficiency. The goal of arm motion planning is to generate feasible and collision free paths that enable humanoid robot to manipulate objects or perform specific actions. This process typically involves several steps including perception, motion planning and control. In order for the humanoid robot to sense the objects in human environment and automatically perform desired action, the implementation of fundamental components are also required. Here we will also focus on avoiding obstacles and improving human-robot interaction. The system will include several components like fast stereo vision to calculate distances accurately in environment, then storing the outcome in order to create an approximate 3D model probabilistically and ultimately search for a collision free path using PRM search method. The combination of these three components will enable the robot to grasp an indicated target object automatically.

Generating 3D images of surroundings

We will estimate the information of depth or the 3D structure of the surrounding from a 2D image or collection of such images. This process is called Depth map Generation. Such maps are useful in computer vision, augmented reality, virtual reality and 3D reconstruction. By incorporating depth information into planning process, the robot can perceive 3D structure of the environment better and hence can make more informed decisions and perform tasks more efficiently. We will be taking the arm length and hand size of the robot about 60 cm and 15 cm respectively, so we require approximately 1cm accuracy in 1m distance with 10Hz calculation rate in order to grasp target object by humanoid robots. To obtain depth maps for motion planning, the robot arm requires a depth sensing system like stereo camera, depth camera or a combination of multiple sensors.

A) Stereo Camera: On analyzing the disparity between corresponding points in a pair of stereo images, we can infer the depth information, allowing for the creation of a disparity map. This map will provide valuable data about the 3D structure of the environment which will aid in motion planning. We will assume that no horizontal disparity occurs for two images and our target will be to detect the occlusion region by comparing the two images.

B) Image Rectification: To make the stereo matching process simpler, the stereo images are rectified. On rectification, the epipolar lines of the image will be aligned making the disparity calculation more efficient.

Correction of geometric distortions and adjusting the image orientation and alignment will also be involved.

C) Direct Depth generation: Depth maps will be generated directly on the surface of the human's body. This technique is useful in scenarios where the humanoid robot need to interact or handle objects on human body like in healthcare, rehabilitation or assisting applications. Attempts has been made to develop an algorithm to check the consistency of the system.

D) Online state monitoring algorithm: During the execution of the planned trajectory, we need to monitor the robot arm state continuously in real time to obtain the best matching region. We can deal with unreliable matching in an online consistency check. This implies that the robot's arm state estimation or sensor measurement may contain errors or inaccuracies that can ultimately affect the consistency check. The methods to be used are:

1) For the two images, set a region from left image (say A) and search in the right image for the best match region and set it as B (say).

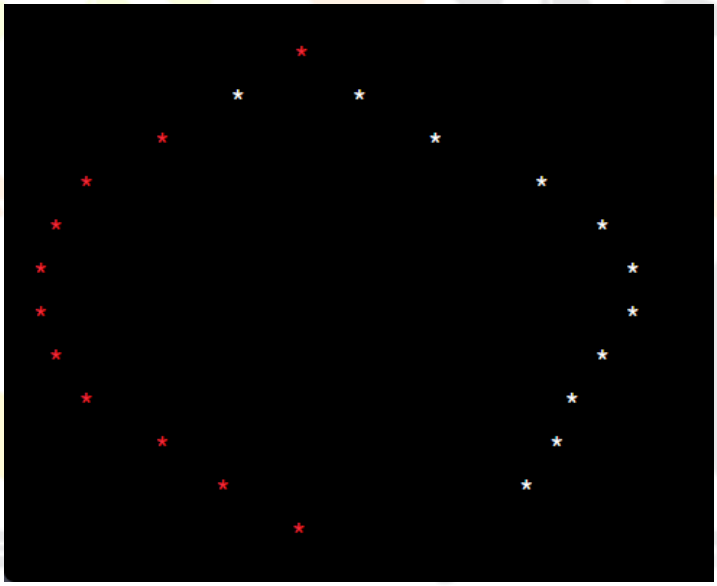
2) Now, by setting region B as reference, search the left image for best match region and set it as C (say).

3) If region A and C are the same region, then we can say that the system is reliable.

Repeat the consistency check at regular intervals or whenever significant changes occur in the state of the robot's arm to avoid consumption of additional memory. The constraints need to be satisfied and calculated during motion planning. These values will enable the first two steps of consistency checking to produce value simultaneously and then the third step calculates the best match. By incorporating the algorithm, the humanoid robot can adapt to real time conditions and hence avoid potential collisions and disturbances during motion planning and execution. This increases safety, reliability and performance and reduces the additional computational cost.

E) Sensor Placement and Calibration: The sensors need to be appropriately placed on the robot's arm to achieve the optimal coverage of the body surface. Calibration of the sensors is essential to determine the position and orientation accurately. Calibration will ensure accurate depth measurement and alignment between robot arm's coordinates and sensor's coordinates.

F) Task execution and adaptation: The depth maps help in execution of tasks and adapting it. By continuously updating the depth maps while operating, the robot arm can adapt its movements and grasp points to the changing body surface. This ability is useful when the person's posture or position varies over time.



The asterisk(*) indicates the robot's arm position while the space represents depth or distance information.

Mesh Modeling

In order to incorporate uncertainties and enable more robust decision-making in dynamic environments, a probabilistic mesh model can be utilized. The environment surrounding the robot arm is represented as a mesh, where each element represents a small volume or surface segment in the environment. The results of the stereo cameras cannot be merged directly as stereo method has reciprocal relationship with distance and resolution.

A) Uncertainty-Aware Planning: The probabilistic mesh model enables uncertainty-aware motion planning. The

planner can consider occupancy probabilities of mesh element rather than assuming static and perfect environment. With the help of stereo vision, we can obtain the nearest point on the view line and obtain projection of environment into 2D image sensor. So, in order to obtain a true model of the environment, we are omitting mesh with smaller view angle and larger surface area.

B) Sampling and optimization: On construction of the roadmap, path optimization techniques are to be applied to find high quality paths between start and goal configurations. Probabilistic sampling techniques such as PRM (Probabilistic Roadmap) will be used in this paper to generate random samples and configurations in the mesh. This will enable minimizing path length, joint angle or energy consumption.

C) Refinement of the Mesh: The samples which are found to be in collision with the obstacles are used to refine the mesh. New cells are added to the mesh in the regions where collisions occur, leading to a more detailed representation of the configuration space in those areas. This mesh refinement and sampling are repeated continuously. The refined mesh is constructed incrementally as the planning algorithm progresses and are checked for collisions. This process continues until a feasible path is obtained from the start to the goal position. The incremental update of the mesh model V(v) is given by the equation,

$$\begin{aligned} V_M(\boldsymbol{v}) &= \frac{W_{M-1}(\boldsymbol{v})V_{M-1}(\boldsymbol{v}) + w_M(\boldsymbol{v})Z_M(\boldsymbol{v})}{W_{M-1}(\boldsymbol{v}) + w_M(\boldsymbol{v})} \quad (2) \\ W_M(\boldsymbol{v}) &= W_{M-1}(\boldsymbol{v}) + w_M(\boldsymbol{v}) \end{aligned}$$

$W_M(v)$ denotes the model length and Z_M is computed for M depth map.

PRM Algorithm for Motion Planning

The PRM algorithm constructs a roadmap in the configuration space of the robot arm by sampling random configurations and connecting them to form a graph. This algorithm is probabilistic in nature as it samples random configurations to construct a roadmap. It is capable of handling complex robot arms with high dimensional configuration space and hence effective planning of collision free paths can be done.

```
PRM_Connect(start, goal, K, r):
graph = EmptyGraph()
AddNode(graph, start)
AddNode(graph, goal)

for i = 1 to K:
  q_rand = SampleRandomConfig()
  if not Collides(q_rand):
    AddNode(graph, q_rand)
    q_near = NearestNeighbor(graph, q_rand, r)
    if not CollidesPath(q_near, q_rand):
      AddEdge(graph, q_near, q_rand)

path = FindPath(graph, start, goal)
return path
```

The algorithm begins with the inclusion of start and end configurations to the graph. It then iteratively samples random configurations and checks if they are collision free. If this configuration is collision free, it is as added as node to the graph. The algorithm then finds the nearest neighbour of the sampled configuration within a radius 'r' and checks if a collision free path exists between near and random configurations (**q_near** and **q_rand** respectively). If this happens, then an edge is added to the graph. Once the graph is constructed, the algorithm searches for a path from start to the goal configuration and this resulting path is the output of the algorithm.

Modified PRM Search Algorithm for Motion Planning

For a modified PRM search algorithm, we will consider incorporating additional enhancements or optimizations to improve the efficiency or quality of the motion planning.

```
Modified_PRM_Connect(start, goal, K, r, max_neighbors):
graph = EmptyGraph()
AddNode(graph, start)
AddNode(graph, goal)

for i = 1 to K:
   q_rand = SampleRandomConfig()
   if not Collides(q_rand):
      AddNode(graph, q_rand)
      q_near = NearestNeighbors(graph, q_rand, r, max_neighbors)
      for q_n in q_near:
         if not CollidesPath(q_n, q_rand):
            AddEdge(graph, q_n, q_rand)

path = FindPath(graph, start, goal)
return path
```

The basic steps remain the same except an additional parameter 'max_neighbors' has been introduced which will limit the number of nearest neighbours considered for connecting a sampled configuration. This modification will control the density of the graph and reduce computational complexity. The random samples are sampled, collision checked and added as nodes to the graph. Nearest neighbours are found within a radius and limited to 'max_neighbors.

Modified PRM Search Algorithm for Motion Planning

This paper proposes a 3D vision-based collision free arm motion planning system as one of the low-level autonomous functions needed for humanoid robots. We used PRM search algorithm to obtain the feasible path between start and goal configuration. This algorithm employed random sampling techniques to explore the configuration space, utilized collision check algorithm to ensure that the path and configurations are collision free so that it can handle high dimensional configuration spaces. Hence, we will get an optimal or near optimal path taking into consideration factors such as distance or edge costs.

This paper includes work on the limitations of the PRM search for motion planning such as the density of the roadmap is controlled as the quality of PRM solution depends on it. The modified search algorithm also reduces computational complexity and the system is applicable in complex dynamic environments. The parameters are perfectly tuned to obtain optimal performance of the robot arm.

In practice, PRM based motion planning will provide humanoid robots a flexible and probabilistic framework for arm motion and will also provide a balance between exploration and exploitation of the configuration space to find feasible and optimal path while considering collision constraints. Also in this paper, target posture is given directly by the operator so that target finding and feedback in final phase functions are required in practical usage.

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