Year	2004	2005	2007	2008
Authors	Okada, K.; Haneda, A.; Nakai, H.; Inaba, M.; Inoue, H.	Stilman, Mike; Kuffner, James J.	Stilman, Mike; Nishiwaki, Koichi; Kagami, Satoshi; Kuffner, James J.	Stilman, Mike; Kuffner, James
Title	Environment manipulation planner for humanoid robots using task graph that generates action sequence	Navigation among movable obstacles: real-time reasoning in complex environments	Planning and executing navigation among movable obstacles	Planning Among Movable Obstacles with Artificial Constraints
Conference / Journal	2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)	International Journal of Humanoid Robotics	Advanced Robotics	The International Journal of Robotics Research
Filename (bibtex id)	okada_environment_2004	stilman_navigation_2005	stilman_planning_2007	stilman_planning_2008
Reference	[35]	[34]	[31]	[29]
HYPOTHESES				
Knowledge of the environment	3D metric map, complete with perfect data.	2D metric map, complete with perfect data.	3D metric map, partial with nearly perfect data. Object poses are estimated at 30 Hzb a global tracking system using markers and infrared cameras. This system also tracks the robot, that brings extra data with its embedded encoders and force sensors.	2D metric map, complete with perfect data.
Obstacle characteristics	Walls, tables, chairs with wheelcasters, cardboard boxes and trash cans. Simplified into rectangular cuboids. No autonomously moving obstacles. Path planning done on a 2D projection from above. Movable obstacles have extra semantic data associated with them: “grasping points”, weight et a pre-registered procedure to move them. Obstacles can be moved in 2D configuration space, in translation and rotation movements.	Walls, round and rectangular tables, loveseats, sofas and chairs. No autonomously moving obstacles. Path planning done with the 2D metric map. Movable obstacles have extra semantic data associated with them: mass center, mass and center of mass. Obstacles can be moved in 2D configuration space, in translation and rotation movements.	Walls, rectangular tables and chairs with wheelcasters. No autonomously moving obstacles. Path planning done on a 2D projection from above with a computation of the convex hull of the 3D mesh. Movable obstacles have extra semantic data associated with them: “grasping points”, mass et center of mass. Obstacles can be moved in 2D configuration space, in translation only, and for heavy objects, only according to the perpendicular axis to the contact line.	Walls, round and rectangular tables, loveseats, sofas and chairs. No autonomously moving obstacles. Path planning done on a 2D occupancy grid, rasterized from the 2D metric map with convex hull of obstacle geometric representation. Movable obstacles have extra semantic data associated with them: mass, center of mass and inertial moment. Obstacles can be moved in 2D configuration space, in translation and rotation movements.
Robot characteristics	Simulated HRP2 Robot (characteristics: http://global.kawada.jp/mechatronics/hrp2.html) with unlimited field of vision. ECan move in a 2D configuration space, in translation and rotation. The robot can lift & drop obstacles.	Nondescript simulated humanoïd robot with unlimited field of vision. Can move in a 2D configuration space, in translation and rotation. The robot can push & pull obstacles.	Real HRP2 Robot (characteristics: http://global.kawada.jp/mechatronics/hrp2.html) with unlimited field of vision obtained through global tracking systeme path planning. Can move in a 2D configuration space, in translation and rotation. The robot can push & pull obstacles.	Same as stilman_navigation_2005.
Problem class	Not explicit but probably a subset of L1.	L1.	L1.	LkM.

Year	2010	2010	2013	2013
Authors	Wu, Hai-Ning; Levihn, M.; Stilman, M.	Kakiuchi, Y.; Ueda, R.; Kobayashi, K.; Okada, K.; Inaba, M.	Levihn, M.; Kaelbling, L. P.; Lozano-Pérez, T.; Stilman, M.	Levihn, M.; Scholz, J.; Stilman, M.
Title	Navigation Among Movable Obstacles in unknown environments	Working with movable obstacles using on-line environment perception reconstruction using active sensing and color range sensor	Foresight and reconsideration in hierarchical planning and execution	Planning with movable obstacles in continuous environments with uncertain dynamics
Conference / Journal	2010 IEEE/RSJ International Conference on Intelligent Robots and Systems	2010 IEEE/RSJ International Conference on Intelligent Robots and Systems	2013 IEEE/RSJ International Conference on Intelligent Robots and Systems	2013 IEEE International Conference on Robotics and Automation
Filename (bibtex id)	wu_navigation_2010	kakiuchi_working_2010	levihn_foresight_2013	levihn_planning_2013
Reference	[25]	[23]	[16]	[15]
HYPOTHESES				
Knowledge of the environment	2D metric map, unknown with perfect data. Hypothesis of unknown space is free space.	3D metric map, unknown with approximative data. The environment configuration is obtained only through onboard sensors. Hypothesis of unknown space is free space.	3D metric map, partial with approximative data (unmovable objects known, movable objects unknown).	Non-discretized 2D metric map, complete with approximative data.
Obstacle characteristics	Rectangular cuboids. No autonomously moving obstacles. No extra semantic data on obstacles. Path planning done on a 2D occupancy grid, rasterized from the 2D metric map. Obstacles can only be moved in 2D configuration space, in translation only along the axes of the plane.	Walls, static rectangular tables and chairs with wheelcasters. No autonomously moving obstacles. No extra semantic data on obstacles. Path planning done on a 2D projection from above with a computation of the convex hull of the 3D mesh that is previously reduced to a prism. Obstacles can be moved in 2D configuration space, in translation only and in a single direction.	Walls, static rectangular tables, carboard boxes and chairs with wheelcasters. No autonomously moving obstacles. No extra semantic data on obstacles. Path planning done on a 2D projection from above. Obstacles can be moved in 2D configuration space, in translation and rotation movements.	Walls, round tables, rectangular loveseats. No autonomously moving obstacles. Path planning done on the 2D non-discretized map. Movable obstacles have extra semantic data associated with them: mass, center of mass, cinematics or frictions (which are determined online through manipulation). Obstacles can be moved in 2D configuration space, in translation and rotation movements.
Robot characteristics	Nondescript simulated wheeled robot with a limited field of vision. Can move in a 2D configuration space, in translation and rotation. The robot can only push obstacles.	Real HRP2 Robot (characteristics: http://global.kawada.jp/mechatronics/hrp2.html) with onboard limited field of vision (Swissranger SR-400: http://www.realtechsupport.org/UB/SR/range_finding/SR4000_SR4500_Manual.pdf and Pointgray Flea2: https://eu.ptgrey.com/support/downloads/10117). Can move in a 2D configuration space, in translation and rotation. The robot can push obstacles.	PR2 Robot (characteritics: http://www.willowgarage.com/pages/pr2/specs) with onboard limited field of vision (Microsoft Kinect V1). Can move in a 2D configuration space, in translation and rotation. The robot can push obstacles.	Simulated humanoïd robot GOLEM KRANG (characteristics: http://www.golems.org/projects/krang.html) with unlimited field of vision. Can move in a 2D configuration space, in translation and rotation. The robot can pull or push obstacles.
Problem class	Subset of L1 since a plan can only contain the manipulation of one obstacle.	Subset of L1 : the robot does not seek to move an obstacle if it can reach its goal without manipulating any obstacle.	Not explicit but probably LkM according to the explanations.	Not explicit but probably L1 according to the explanations.

Year	2014	2014	2015	2016
Authors	Levihn, M.; Stilman, M.; Christensen, H.	Clingerman, C.; Lee, D. D.	Clingerman, C.; Wei, P. J.; Lee, D. D.	Scholz, J.; Jindal, N.; Levihn, M.; Isbell, C. L.; Christensen, H. I.
Title	Locally optimal navigation among movable obstacles in unknown environments	Estimating manipulability of unknown obstacles for navigation in indoor environments	Dynamic and probabilistic estimation of manipulable obstacles for indoor navigation	Navigation Among Movable Obstacles with learned dynamic constraints
Conference / Journal	2014 IEEE-RAS International Conference on Humanoid Robots	2014 IEEE International Conference on Robotics and Automation (ICRA)	2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)	2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
Filename (bibtex id)	levihn_locally_2014	clingerman_estimating_2014	clingerman_dynamic_2015	scholz_navigation_2016
Reference	[11]	[10]	[7]	[4]
HYPOTHESES				
Knowledge of the environment	2D metric map, unknown with perfect data. Hypothesis of unknown space is free space.	2D costmap, unknown with approximative data. Hypothesis of unknown space is free space.	Same as clingerman_estimating_2014, but the map representation in memory grows only when new areas are explored to gain computing performance.	Non-discretized 2D metric map, complete with approximative data.
Obstacle characteristics	Walls, round tables, rectangular loveseats. No autonomously moving obstacles. No extra semantic data on obstacles. Obstacles can be moved in 2D configuration space, in translation only in a single direction.	Walls, static heavy cardboard boxes, chair with wheelcasters. No autonomously moving obstacles. No extra semantic data on obstacles. Path planning done on the 2D discretized costmap. Obstacles can be moved in 2D configuration space, in translation only in a single direction.	Same as clingerman_estimating_2014 but the use of D*Lite allows to take autonomously moving obstacles into account.	Same as scholz_navigation_2016.
Robot characteristics	Nondescript simulated wheeled robot with a limited field of vision. Can move in a 2D configuration space, in translation and rotation. The robot can push & pull obstacles.	Custom robot vehicle for MAGIC 2010 Competition, assimilable to an RC car, with a limited conic field of vision obtained through the fusion of data between a RGB camera and a LIDAR projecting to a distance of up to 10m. An embedded IMU and wheel encoders help localize the robot. A front bumper is used to push the obstacles. Can move in a 2D configuration space, in translation and rotation. The robot can push obstacles.	Same as clingerman_estimating_2014.	Real humanoïd robot GOLEM KRANG (characteristics: http://www.golems.org/projects/krang.html) with unlimited field of vision obtained through an external camera positioning system. Can move in a 2D configuration space, in translation and rotation. The robot can pull or push obstacles.
Problem class	Subset of L1 since a plan can only contain the manipulation of one obstacle.	Not explicit but probably a subset of L1.	Same as clingerman_estimating_2014.	Not explicit but probably L1 according to the explanations.

Filename (bibtex id)	okada_environment_2004	stilman_navigation_2005	stilman_planning_2007	stilman_planning_2008
Reference	[35]	[34]	[31]	[29]
APPROACHES				
Path Planning Algorithm(s) and heuristics	No explicit mention.	A* subroutine. A motion planner heuristic is introduced to improve performance but is not admissible (only “well-informed”). Use a grid-search type subroutine that considers collisions as soft constraints to find disjoint regions and obstacles to move in priority.	Same as stilman_navigation_2005.	For a transit path (no obstacle manipulation), A* is used with a euclidean heuristic augmented with a single penalty if the path penetrates the configuration space of the previously artificially constrained obstacle. For a transit path (with obstacle manipulation), a BFS algorithm is used with a heuristic that penalizes the penetration of a movable obstacle’s configuration space.
Evaluation and evolution of an obstacle’s "movable" characteristic and its associated cost	No online evaluation of the “movable” characteritic of an obstacle, this is already known since the beginning. The cost of moving an obstacle is defined as the energy necessary to move its weigth.	No online evaluation of the “movable” characteritic of an obstacle, this is already known since the beginning. The cost of moving an obstacle is defined as the energy necessary to move its weigth.	Same as stilman_navigation_2005.	No online evaluation of the “movable” characteritic of an obstacle, this is already known since the beginning. No particular cost of moving the obstacle except the cost of the movement itself.
Object manipulation maneuver planning	The kinematic/friction constraints of the object are not taken into account. The placement of the robot explicitly depends on pre-determined “grasping points” that depend on the obstacle geometric configuration.	The kinematic/friction constraints of the object are not taken into account. The placement of the robot explicitly depends on pre-determined “contact points” that depend on the obstacle geometric configuration.	The friction constraints of the object are mildly taken into account by locally adaptating the object’s prehension and the robot’s posture to keep it on the expected trajectory. The placement of the robot explicitly depends on pre-determined “contact points” that depend on the obstacle geometric configuration.	The kinematic/friction constraints of the object are not taken into account. The placement of the robot explicitly depends on pre-determined “contact points” that depend on the obstacle geometric configuration.
Planning taking uncertainty into account	None.	None.	Uncertainty is managed through continuous verification of confimity to the generated plan and replanning are triggered whenever necessary. The approach and grasping procedures are progressive and allow to adjust the robot pose locally to improve the chances of successful manipulation.	None.
PERFORMANCE CRITERIA				
Evaluation in a simulated/real setting	Simulation.	Simulation.	Real.	Simulation.
Computation time	No performance statements : will suppose that is not usable in real-time.	Usable in real-time if heuristic is used.	Usable in real-time.	Usable in real-time.
Optimality and completeness	No guaranteed optimality. No guaranteed completeness.	Guaranteed global optimality if heuristic is not used. Guaranteed completeness in any case.	No guaranteed optimality. Guaranteed completeness.	No guaranteed optimality. No guaranteed completeness.
Optimality target	Distance or energy.	Number of moved obstacles and energy.	Energy.	Distance and minimal traversal of the movable obstacles configuration spaces.
Social acceptability	No interactions with human beings nor consideration of social norms.	Mentions the possibility of taking into account the risk of moving an obstacle because of its fragility, but does not propose anything to deal with this.	No interactions with human beings nor consideration of social norms.	No interactions with human beings nor consideration of social norms.
Number and Density of obstacles	No statements. May suppose a maximal number of movable obstacles < 10 from the figures.	Maximal tested number of movable obstacles = 90.	Maximal tested number of movable obstacles = 10.	Maximal tested number of movable obstacles = 9.

Filename (bibtex id)	wu_navigation_2010	kakiuchi_working_2010	levihn_foresight_2013	levihn_planning_2013
Reference	[25]	[23]	[16]	[15]
APPROACHES				
Path Planning Algorithm(s) and heuristics	A* path finding subroutine with a euclidean distance heuristic. The overall algorithm also uses a heuristic to determine the order in which to evaluate obstacles and another to stop plan evaluations when no lower cost plan including a specific obstacle can be found. One of the heuristic destroys optimality.	RRT (Rapidly exploring Random Tree) path finding algorithm. No particular heuristic is mentioned.	RRT (Rapidly exploring Random Tree) path finding algorithm. No particular heuristic is mentioned. Use of a “peephole optimization” method to execute the elements of a computed plan in a more efficient way.	Uses RRT variations: KDRRT (Kinodynamic-RRT) and FPRRT (Low-Dimensional RRT). No particular heuristic is mentioned.
Evaluation and evolution of an obstacle’s "movable" characteristic and its associated cost	An obstacle is considered movable until a manipulation fails, it is then considered blocked. The cost of moving an obstacle is a pre-determined constant multiplied by the manipulation path length : depending on the dimension of the constant, this computation could be assimilated to an energy or a time.	An obstacle is considered movable until a manipulation fails, it is then considered blocked. No particular cost of moving the obstacle except the cost of the movement itself.	All initially known obstacles are tagged as static. Any detected obstacle is identified through computer vision during navigation and is deemed movable or not then. No particular cost of moving the obstacle except the cost of the movement itself.	An obstacle is considered movable until a manipulation fails, it is then considered blocked.
Object manipulation maneuver planning	The kinematic/friction constraints of the object are not taken into account. The placement of the robot does not explicitly depend on pre-determined “contact points”, but the figures and experimental video show that such points are used in the implementation because the robot systematically enters in contact with the center of the manipulated obstacle’s side.	The kinematic/friction constraints of the object are not taken into account. The placement of the robot does not depend on pre-determined but on dynamically computed “grasping points”, that are situated at the middle of the top sides of the moved object.	The kinematic/friction constraints of the object are not taken into account. The placement of the robot does not explicitly depend on pre-determined “contact points”, but it can be infered from the experimental video material that they actually use them.	The kinematic/friction constraints are taken into account, which is one of the main points of the algorithm. The placement of the robot explicitly depends on pre-determined “grasping poses” that depend on the obstacle geometric configuration.
Planning taking uncertainty into account	None.	A probabilistic model is used to determine the configuration of obstacles from the perceived point cloud. Use of an algorithm named “color-ICP” to estimate the movement of the obstacle as it is moved by the robot.	Use of an “Unscented Kalman Filter” to estimate the relative poses of the robot to the objects, and the unknown space is actually treated differently than free space through a “war fog”: the algorithm actually checks if it has sufficiently observed the environment in order to act. Also use a probabilistic technique of “e-shadows” to associate a heuristic cost of traversing a zone near an obstacle. Waypoints are distributed in the map to reduce positioning error .	Use of PRM (Probabilistic RoadMaps) to create a navigation subgraph for every free-space zone. A Markov Decision Process is created from the PRM, to manage the possibility of manipulation failures. Monte Carlo simulations in physics engine allow to estimate the success probabilities of a manipulation action.
PERFORMANCE CRITERIA				
Evaluation in a simulated/real setting	Simulation.	Real.	Real.	Simulation.
Computation time	Usable in real-time.	Usable in real-time.	Usable in real-time.	Not usable in real-time.
Optimality and completeness	No guaranteed optimality. No guaranteed completeness.	No guaranteed optimality. No guaranteed completeness.	No guaranteed optimality but has been improved compared to previous implementations of BHPN. No guaranteed completeness.	Guaranteed optimality with error epsilon. Guaranteed completeness if epsilon = 0.
Optimality target	Energy.	Distance and minimal number of moved obstacles.	Probability of reaching the goal and Distance.	Time, energy and probabiblity of succeding in a manipulation.
Social acceptability	No interactions with human beings nor consideration of social norms.	Mentions the possibility of taking into account the risk of moving an obstacle because of its fragility, but does not propose anything to deal with this.	No interactions with human beings nor consideration of social norms.	No interactions with human beings nor consideration of social norms.
Number and Density of obstacles	Maximal tested number of movable obstacles = 20.	Maximal tested number of movable obstacles = 3.	Maximal tested number of movable obstacles = 14.	Maximal tested number of movable obstacles = 30.

Filename (bibtex id)	levihn_locally_2014	clingerman_estimating_2014	clingerman_dynamic_2015	scholz_navigation_2016
Reference	[11]	[10]	[7]	[4]
APPROACHES		\		
Path Planning Algorithm(s) and heuristics	Uses a D* Lite path finding subroutine. The overall algorithm also uses a heuristic to determine the order in which to evaluate obstacles and another to stop plan evaluations when no lower cost plan including a specific obstacle can be found. The heuristics no longer destroy optimality.	ARA* algorithm with a euclidean distance heuristic. Also uses a Lower Confidence Bound (LCB) instead of a heuristic sum to make the algorithm more “exploratory”.	D-Lite* algorithm with a euclidean distance heuristic. Also uses a Lower Confidence Bound (LCB) instead of a heuristic sum to make the algorithm more “exploratory”.	RRT + model-dependent manipulation policy.
Evaluation and evolution of an obstacle’s "movable" characteristic and its associated cost	An obstacle is considered movable until a manipulation fails, it is then considered blocked. The cost of moving an obstacle is a pre-determined constant multiplied by the manipulation path length : depending on the dimension of the constant, this computation could be assimilated to an energy or a time.	The estimation of the cost of manipulating an obstacle is done while navigating and is based off the results tentative interaction to obstacles with similat visual features. This is translated by a cost random variable that has a normal distribution. By default, at the beginning of the experiment (before any sort of learning), any obstacle is considered potentially movable (even walls). If through interaction, an obstacle is deemed movable in a specific direction, it is supposed to be movable in any direction. The cost values depend on a ratio between measured reverse speed and expected reverse speed.	Same as clingerman_estimating_2014, but the random variable has a gamma distribution.	Same as scholz_navigation_2016.
Object manipulation maneuver planning	The kinematic/friction constraints of the object are not taken into account. The placement of the robot does not explicitly depend on pre-determined “contact points”, but the figures and experimental video show that such points are used in the implementation because the robot systematically enters in contact with the center of the manipulated obstacle’s side.	The kinematic/friction constraints of the object are not taken into account. The placement of the robot does not depend on “contact points”.	Same as clingerman_estimating_2014.	The kinematic/friction constraints are taken into account, which is one of the main points of the algorithm. The placement of the robot explicitly depends on pre-determined “grasping points” that depend on the obstacle geometric configuration.
Planning taking uncertainty into account	None.	The occupancy grid costmap integrates the notion of uncertainty directly. Probabilistic models are used to map the RGB sensors date with with the movability status of a cell. A Kalman filter is also used to update the cost distribution associated with a cell. Regular pauses in the robot’s movement allow for positioning recalibration.	Same as clingerman_estimating_2014.	Same as scholz_navigation_2016 + PBRL (Physics-Based Reinforcment Learning) to manage a great variety of manipulation cases.
PERFORMANCE CRITERIA				
Evaluation in a simulated/real setting	Simulation.	Real.	Same as clingerman_estimating_2014.	Real.
Computation time	Usable in real-time.	Usable in real-time.	Same as clingerman_estimating_2014.	Usable in real-time.
Optimality and completeness	Guaranteed local optimality. No guaranteed completeness.	No guaranteed optimality. No guaranteed completeness.	Same as clingerman_estimating_2014.	Same as scholz_navigation_2016.
Optimality target	Energy.	Time.	Fusion between distance, time and rotation cost.	Time, force and moment.
Social acceptability	No interactions with human beings nor consideration of social norms.	No interactions with human beings nor consideration of social norms.	Same as clingerman_estimating_2014.	Same as scholz_navigation_2016.
Number and Density of obstacles	Maximal tested number of movable obstacles = 70.	Maximal tested number of movable obstacles = 3.	Same as clingerman_estimating_2014.	Maximal tested number of movable obstacles = 2.