Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

Article

Applied Robot Coverage Path Planning with Multiple Decision Making Capability under Uncertainty using Knowledge Inference with Hedge Algebras

Hai Van Pham [1], Philip Moore [2]*

[1] School of Information Technology and Communication, Hanoi University of Science and Technology, Hanoi, Vietnam; haipv@soict.hust.edu.vn

[2] School of Information Science and Engineering, Lanzhou University, Lanzhou 730030, Gansu Sheng, China; philip.moore@outlook.com

* Correspondence: philip.moore@outlook.com

Abstract: Robotic decision-support systems must facilitate a robots interactions with their environment, this demands adaptability. Adaptability relates to awareness of the environment and 'self-awareness', human behaviour exemplifies the concept of awareness to arrive at an optimal choice of action or decision based on reasoning and inference with learned preferences. A similar conceptual approach is required to implement awareness in autonomous robotic systems which must adapt to the current dynamic environment (the context of use). By incorporating 'self-awareness' with knowledge of a Robot's preferences (in decision making) the decision maker interface should adapt to the current context of use. This paper proposes a novel approach to enable an autonomous robotics which implements path planning combining adaptation with knowledge reasoning techniques and hedge algebra to enable an autonomous robot to realise optimal coverage path planning under dynamic uncertainty. The results for a cleaning robot show that using our proposed approach demonstrated the capability to avoid both static and dynamic obstacles while achieving optimal path planning with increased efficiency. The proposed approach achieves the multiple decision-making objectives (path planning) with a high-coverage and low repetition rates. Compared to other current approaches, the proposed approach has demonstrated improved performance over the conventional robot control algorithms.

Keywords: robotics; coverage path-planning; knowledge reasoning and inference; hedge algebras; decision-support systems

1. Introduction

Robotics have become essential in industry where improved efficiency and quality control in the manufacturing process is essential to a manufacturers commercial success. However, when employed in the manufacturing process robots are generally pre-programmed with limited decision-making capability. Robotic decision-support systems designed for use in multiple domains must facilitate a robot's interactions with their environment and facilitate the required actions and behaviour, this demands adaptability. Adaptability relates to awareness of the environment and 'self-awareness', human behaviour exemplifies the concept of awareness to arrive at an optimal choice of action or decision based on reasoning and inference with learned preferences. A similar conceptual approach is required to implement awareness in autonomous robotic systems which must adapt to the current dynamic environment (the context of use). By incorporating 'self-awareness' with knowledge of a Robot's preferences (in decision making) the robots decision maker interface cab adapt to the current context of use.

Mobile robots must be 'self-aware'. For example, a mobile robot will generally be battery powered and its awareness will include both knowledge of the defined operating environment and its current

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

'state' which will include the battery condition. The robot's knowledge of these parameters and the operating environment will enable the robot to return automatically to its charging point as required.

While robotic systems are now ubiquitous in the industrial context, such systems are gaining traction in multiple domains where autonomous operation is desired, a central requirement for mobile robotic systems is the identification of *coverage path-planning* (CPP). In environmental dynamics, mobile robots are increasingly being employed to performing complex tasks in dynamic environments. However, uncertainty is present in robots awareness due to environmental dynamics, imprecision in control, imperfect sensing and localisation, and unpredictability. The primary of objective of robotics is to provide an 'experience set' to accommodate environmental dynamics under uncertainty, this relates to all knowledge, skills and attitudes for the control, application, and operation of robots. Robotics may be considered as an 'innovation technology', research into such technologies provides information and instructions for engineers capable of formalising problems and developing algorithmic solutions that will generalise in a wide class of computing problems to facilitate production automation [in robotics] [1]. The approach proposed in this paper can be simply applied to both static and dynamic environments.

Turning to 'real-world' practical problems, the cleaning task represents a significant path planning problem, in this paper we address path planning implemented in a cleaning robot. Cleaning may be undertaken in a domestic environment but there are also many use-cases where cleaning may be required in restricted spaces; such spaces may have limited access and/or have toxic contamination/pollution and are therefore not accessible by a human cleaner. An autonomous robot provides a solution for multiple cleaning tasks in a range of domains and environments. A mobile robot has the potential to address the multiplicity of cleaning tasks and if the CPP problem is effectively addressed then efficient cleaning may be achieved.

To enable autonomous robot operation with the capability to implement optimal decision-making in a dynamic environment we have investigated the CPP problem and we have addressed two fundamental scientific questions related to the provision of decision-support for a mobile robot: (a) how a mobile robot can form a high-level probabilistic representation of an operating space (the defined environment), and (b) how a mobile robot can understand and reason about the operating environment and implement the multiple decisions (i.e., tasks) while in motion.

The first question directly addresses the issue relating to feature extraction (the static and dynamic obstacles), the second question may be viewed in terms of special recognition (modelling the operating environment). When considered in unison, these questions address the hierarchical representation we aim to realise. However, such a representation must consider and treat uncertainty (in terms of information) in an appropriate way. Additionally, to fully understand the operating environment, a robot must be capable of conceptualising the operating environment to enable the classification of the environment and wherever possible develop a conceptual model of the dynamic environment.

This paper presents a novel approach to enable the autonomous operation of a cleaning robot which implements CPP. The proposed approach combines robot adaptation with knowledge reasoning and inference techniques and hedge algebra to provide a basis upon which CPP may be achieved under dynamic uncertainty with the capability for a cleaning robot to avoid collision with obstacles in the operating environment. The proposed algorithm is designed to achieve improvements to the STC algorithm combined with reasoning techniques and HA to find the optimal CPP for the defined environment. The robot can apply its available knowledge using rules in the knowledge base to find optimal path, avoid obstacles, and maximize coverage. The experimental results show that using our proposed approach the robot demonstrated the capability to avoid both static and dynamic (moving) obstacles while achieving optimal path planning thus reducing both computational cost and time. As compared to other current approaches, the proposed approach achieves the multiple decision-making objectives (path planning) with a high coverage rate and low repetition rate in covering a defined area. The proposed approach has demonstrated improved performance over the conventional robot control algorithms.

 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at *Machines* **2018**, *6*, 46; doi:10.3390/machines6040046

The remainder of this paper is structured as follows: in Section 2 we consider related research as it relates to CPP. The problem formulation using hedge algebras is addressed in Section 3 along with consideration of intelligent support for CPP and quantitative semantic mapping. The proposed CPP model is presented in Section 4 with the path planning processing algorithm. Evaluation is addressed in Section 5 with a case study using hedge algebras with multiple decision-making objectives; the experimental results are considered in Section 6 with an evaluation and a comparative analysis. Section 7 presents a discussion which considers machine cognition as it relates to entities (which include both humans and intelligent robotic systems); potential future directions for research is considered in Section 7.3. The paper closes with concluding observations in Section 8.

2. Related Research

In this section we consider related research as it relates to CPP. There are two general algorithmic approaches to the CPP problem: (a) *classical algorithms*, and (b) *heuristic algorithms*, Figure 1 presents an overview of these approaches [2] [1] [3] [4] [5]. We can see from Figure 1 that *classical* algorithms may be classified under several headings: *cell decomposition*, *potential field*, *sampling-based methods*, and *sub-goal networks*. From Figure 1 we can also see that *heuristic* algorithms may be classified under several headings: *artificial neural networks* (ANN), *fuzzy systems*, *nature inspired algorithms*, and hybrid algorithms. In our research the focus is on a survey of heuristic-based algorithms for CPP.

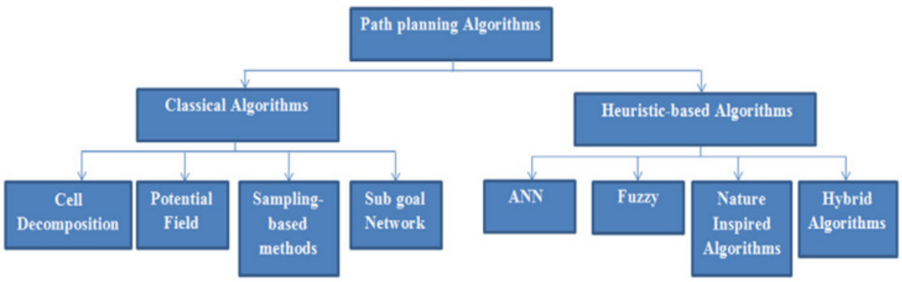

Figure 1. The classification of robot path planning algorithms (source: [4])

Research has considered CPP from several perspectives. As CPP relates to complex surfaces, a robotic needle-punching path planning method is applied to adjust different 'preforms' with different shapes, dimensions and needling distributions as discussed in [3]. An investigation into mobile robotics [6] [7] has shown that CPP can be solved with narrow spaces and a complex map for environments with multiple obstacles. In related studies [8] investigations have contributed a manipulator control and the theoretical ideas on using ANN with reinforcement learning for multiple robotic tasks [8] [9]. In the identification of multiple objects, a new optimal hierarchical global path planning approach for mobile robots is applied in a cluttered environment using particle swarm optimization [10]. Other related Robot studies have utilised ANN [11], decentralized reinforcement learning (DRL) [12], matrix-binary Codes based on genetic algorithms have been applied to enable path planning for mobile robots including manipulator control and the theoretical ideas to solve the CPP problem. Munoz *et al* [13] have proposed a unified framework for path-planning and task-planning for autonomous robots while Patle *et al* [14] have utilised an approach based on matrix-binary codes with a genetic algorithm to implement path planning of mobile robots.

In 'real-world' environments (defined operating spaces), robots will be highly dependent on the ability to understand, interpret, and generate representations of the environment in which they are operating, ideally in both a human and machine-readable formalism [11] [12]. Representation of an entities *'world'* [15] through perception and action is a long standing feature of artificial intelligence research and the "notions of central and peripheral systems evaporate—everything is both central and peripheral" [16]; such concepts apply to robotic interactions with their environment (or *'world'*. An important element in this process lies in decision making with obstacle avoidance to obtain multiple

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

objectives in dynamic environments and identify optimal coverage paths [10] [17]. Robots are now capable of reliably manipulating objects in our daily lives when combined with artificial intelligence (AI) techniques for planning and decision-making, this allows a machine to determine how a task can be completed successfully [9].

CPP algorithms have been implemented in many 'real-world' applications in dynamic environments; examples include: cleaning and monitoring robots, automatic lawn mowers, inspection robots, painting robots, and industrial robots [2] [1] [3] [4] [6] [7] [18] [19] [20] [21] [19] [22] [23]. The CPP problem has multiple goals: full coverage (i.e., every point in the domain is covered and no point is visited multiple times), no overlapping or repetition (no point is visited multiple times), and/or a variety of objectives on the simplicity or the shortest of the paths.

The potential directions for path planning research have been addressed in an interesting study which investigated controlling manipulators using ANN [11] [12]. A study of the value-iteration-based algorithm is effectively applied to multiple robotic tasks [12]. An interactive robot system using psychological phenomena during communication has shown that this approach may provide a basis for suitable decision-support in mobile robotics [24]; this opens a new way for robot adaptation in making decisions in environmental dynamics.

This brief overview of the related research has identified both the potential efficacy of CPP but also that the current approaches fall short in achieving optimal CPP while minimising repeatedly traversing areas within the defined environment. In this paper we present our novel approach to the CPP problem which attempts to address the perceived issues in the related research considered.

3. Problem Formulation using Hedge Algebras

In this section we introduce hedge algebras with intelligent support for robot CPP and quantitative semantic mapping. Hedge Algebras (HA) was proposed by Ho and Wechler in 1990 [25]. Subsequent research has produced many interesting developments of the concept along with successful applications.

3.1. Hedge Algebras with intelligent decision support in Robot CPP Coverage Path Planning

We have developed our approach to enable the simulation of awareness (i.e., using inference and reasoning) with decision-making (by the robot) to provide a basis upon which the robot can monitor the environment and reach optimal CPP decisions. In this section we present for each concept our fuzzy approach, additionally we introduce the structure calculations on the process to simulate human reasoning.

Consider the domain $(T(X))$ of the linguistic variable (X). According to [7] [26] axioms $(T(X))$ may be represented as algebraic structures and symbols $\{AH = (T(X), G, H, \leq)\}$ where (G) is a collection of birth elements of linguistic variable, (H) is a set of hedges, and $(\leq)$ is semantic relation on $(T(X))$. If G containing elements $(0, 1, X)$ is the smallest element, the largest element and neutral element is (X). An algebraic structure $\{AH = (T(X), G, H, \leq)\}$ where $(H = (H^\wedge + \cup H^\wedge -))$ is called a (HA) if the formula satisfies with the following axioms [18] [12]:

1. Each element is either positive or negative for any part in the (HA), including itself;
2. The two elements (u) and (v) are independent, that is $(u \neq H(v))$ AND $(v \neq H(u))$ are comparable with $(\forall x \in H(u))$ AND $(x \in H(v))$. IF (u) AND (v) are not comparable, $THEN$ $(\forall x \in H(u))$ AND $(\forall y \in H(v))$ are NOT comparable;
3. IF $(x \neq h_x)$ $THEN$ $(x \in H(h_x))$ AND IF $(h \neq k)$ AND $(h_x \leq k_x)$ $THEN$ $(h' h_x \leq k' k_x)$ with $(\forall h', k', h, k, \in H)$;
4. IF $(u \in H(v))$ AND $(u \leq v)$ OR $(u \geq v)$ $THEN$ $(u \leq h_v)$ OR $(u \geq h_v)$ where $(\forall h \in H)$;

Set (H) includes positive hedges $(H^\wedge +)$ and negative hedges $(H^\wedge -)$. The positive hedges increase the semantic representation of a word and therefore its impact while negative hedges reduce the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

semantic representation of a word and therefore its impact. Without loss of generality, we always assume that $(H^- = \{h_1 > h_2 \cdots > h_p\})$ AND $(H^+ = \{h_{p+1} < h_{p+2} < \cdots < h_{p+q}\})$.

3.1.1. For Example

Considering the linguistic domain for a Robot of truth variable $TRUTH$, (dom($TRUTH$) = *true*, *false*, *very true*, *very false*, *more true*, *more false*, *little true*, *little false* ...). The (dom($TRUTH$)) may be expressed as an algebraic structure $(AT = ((T(X)), G, H, \leq))$ where:

1. $(T(X))$: is the set linguistic values (dom($TRUTH$);
2. (G): is a set of primitive word – birth elements (*true* ,*false*);
3. (H): is a set of hedges (*very*, *more*, *little*;
4. $(\leq)$: is the semantic relation(s) on 'words' (a fuzzy concept). The semantic relations are the ordered relations derived from the natural language meaning, i.e., $(false \leq true)$, $(moretrue \leq verytrue)$, $(veryfalse \leq moretrue)$, $(possibletrue \leq true)$, $(false \leq possiblefalse)$, $\ldots$.

The set of linguistic values $(T(X))$ is the result derived from (G) by the hedges in (H). Thus, each element $(x \in T(X))$ will be represented. $(x = h_n, h_{n-1}, \ldots h_1 g, G \in G)$. $(H(x))$ is set of elements is resulting from (x). Considering $(V \in H^+(V - very))$, $(L \in H^-(L - little))$, $(g \in G)$ is positive IF $(g \leq Vg)$ and is negative IF $(g \geq Vg)$ (or $(g \in G)$ is positive IF $(g \geq Lg)$ and is negative IF $(g \leq Lg)$if. IF (G) has exactly two fuzzy primitive elements (g^+) and (g^-), then (g^+) is called a positive birth element and (g^-) is called a negative birth element and $(g^- < g^+)$. In the example above, *truth* is positive and $false$ is negative

3.2. *Quantitative semantic mapping*

Where $(HA\ AT = (T(X), G, H, \leq))$ is mapped $(f : T(X) \rightarrow [0,1])$ as a quantitative semantic function on (AT) IF $(\forall h, k \in H^+ OR \forall h, k \in H^- AND \forall x, y \in T(X))$, we have:

$$\left[\frac{f(hx) - f(x)}{f(kx) - f(x)}\right] = \left[\frac{f(hy) - f(y)}{f(ky) - f(y)}\right] \tag{1}$$

With hedge algebras and quantitative semantic functions we can define a concept so abstract and difficult to define satisfactorily in conventional conventional fuzzy set theory where the 'fuzziness' of a fuzzy concept or fuzzy set fails to form an effective representation. Consider the following values: *true*, *false*, *more true*, and *more false* etc; the issue lies in how to define the 'fuzziness' of the linguistic value (we may consider the linguistic values in terms of a spectrum around *truth* and/or *falsity*). Based on the use of hedge algebras, we have a defining visual fuzziness based on the size of $(H(x))$. Given a quantitative semantic function (f) of $(T(X))$, consider that for $(x \in X)$ where the 'fuzziness' of (x) is measured by the diameter of the episode $(f(H(x)) \subseteq [0,1])$. Figure 2 describes the fuzziness of linguistic values.

4. The proposed Coverage Path Planning model

The proposed algorithm is designed to achieve improvements to the STC algorithm combined with reasoning techniques and HA to find the optimal CPP for the defined environment. The robot can apply its available knowledge using rules in the knowledge base to find optimal path, avoid obstacles, and maximize coverage. The proposed model for the on-line robot is shown in Figure 3.

In the proposed CPP model, before releasing the robot in the operating space rules from the knowledge base are programmed into the robot. The rules are created and updated by experts to find the optimal CPP and the approach to cleaning the defined environment. The rules are applied as follows:

1. The robot traverses the operating space visiting all the nodes;

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

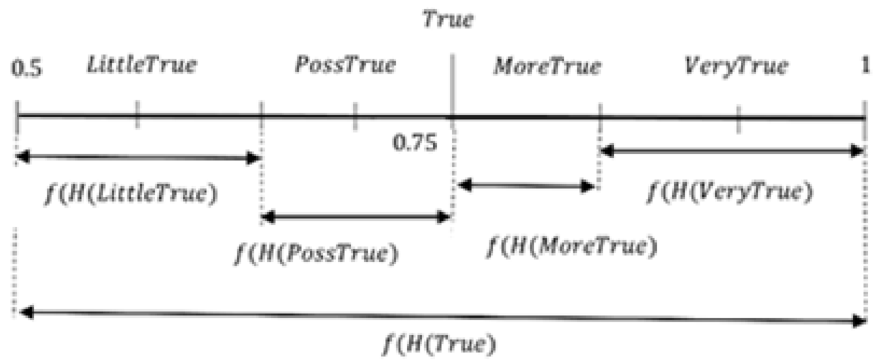

Figure 2. Fuzziness of linguistic values in hedge algebras

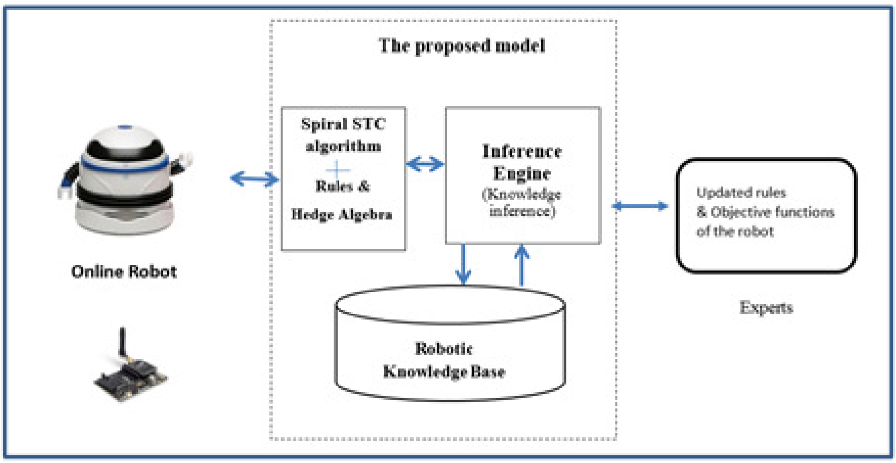

Figure 3. The proposed coverage path planning model for the on-line robot control

2. The robot must visit all the nodes in the operating space (i.e., identify if the nodes(cells) and evaluate if nodes are clear, are occupied by an obstacle(s), or are bounded by walls. The aim is to visit all nodes without repeating or overlapping paths (i.e., to enable the identification of the optimal coverage path);
3. The robot must avoid all static and dynamic (moving) obstacles;
4. The robot will find the 'optimal path' including the uncertainties (a dynamic operating space) with its simple motion trajectories (e.g., straight lines or circles).

4.1. Problem and formulation

1. The *Hedge_DSS_Robot*: the objective optimization function reaches decisions to maximise the operational efficiency of the robot in CPP and enable multiple robot decision making objectives;
2. The *weight* (w_j): representative of (Si) and (w_j), the weight is a value of the linguistic variable that can recognised in the value in range: *important*, *very important*, *more important*, *little important*, *very little important*, *possibly important*, ...;
3. Based on quantitative semantic mapping of (HA), linguistic values for (w_j) fall in the range [0,1]. Means joining in multiple decision-making objectives for the Robot tasks (Si) and where $((Si \cap Sj) = (\theta, \forall i, j \in \{1, 2, \cdots r\}))$;
4. $(Q_j(X))$: is the objective function of multiple decision-making objective. $(Q_j(X))$ recognises the linguistic value of the linguistic variable used in the quantitative semantics mapping of (HA) and transfers the linguistic value in the range [0.1];

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

5. The decision variables (X_{ij}) is binary and defines the tasks for the multiple decision-making objectives;
6. Calculate the objective function value for $(Q_j(X))$

Step 1: Identify the objectives for a moving robot

The CPP model for the *Hedge_DSS_Robot* (HDR) is proposed when identifying multiple objectives as follows:

$$HDR = \frac{Max}{x} \sum w_j . Q_j(X) \tag{2}$$

The constraints include:

1. $\sum_k X_{ik} = 1 \forall i \in N$
2. $\sum_{ie \in s_j us_i} x_{i1} \geq 1$
3. $x_{ik} = \{ \frac{1,\ If\ option\ i\ is\ assigned\ Robot\ to\ mission\ (k)}{0,\ other}$

Step 2. Applied STC algorithm for Robot travel in a graph
Create Recursive STC (w, x): while (x) is a mega-cell containing a start point, (w) is a cell for the previous point.
Initialization: Call STC2 $(Null, S)$ where (S) is the starting cell.
Procedure STC2 (w, x):
(1) Mark the current cell (x) as an old cell;
(2) **While** x has a new free or partially occupied neighbouring cell (Y) where $(x \neq \theta)$:
(a) Scan for the first new neighbour of x in counter-clockwise order, starting with the parent cell w: call this neighbour $(y_j \in Y)$;
(b) Calculate the time from current sub-cell of (x) to sub-cell of destination (y_j) based on Hedge algebra in the time series $((T_j) = (\sum_u t_u))$ and construct a spanning-tree edge from (x) to (y);
(c) Calculate time to estimate obstacles with the nearest y moving to sub-cell destination in the time series $(P_j = (n * t))$;
(d) Consider IF mega-cell (y) satisfies $(MAX\ (P_j - T_j))$;
(e) Move to a sub-cell of (y) along the spanning tree edges using a path determined by the type of edge from (x) to (y) as described in the following steps ;
End of **while** loop.
(f) Execute STC2 (x, y).
(3) IF $(x \neq S)$, move back from (x) to a sub-cell of (y) along a path determined by the type of edge from (x) to (w);
(4) Return. End of STC2 (w, x).

Step 3: Apply reasoning techniques using rules in the Robot knowledge
Consider the rules in reasoning techniques in robot reasoning. The rule form is as shown in Eq. (3):

$$Rule\ i : \left((x_1 = a_1)^\wedge (x_2 = a_2)^\wedge (x_3 = a_3)^\wedge (x_4 = a_4)^\wedge \cdots (x_i = a_i) \right) \rightarrow (c, p) \tag{3}$$

where $(x_i = a_i)$ with operations $(<; >, \leq, \geq)$, (p) is the weight (w_i) of *Rule i* with certain factor weighting (c). In typical rules we can consider reasoning techniques combined with events and as shown in Eq. (4):

$$IF\ \left((c_1, p_1)^\wedge (c_q, p_2)^\wedge (c_3, p_3)^\wedge \cdots (c_i, p_i) \right)\ THEN\ \rightarrow (r, c) \tag{4}$$

where (c_i, p_i) represents an event, weight (w_i), and certain weight (c) of the considered *Rule i*.

Step 4: Process rules with reasoning forward chaining

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

Apply reasoning techniques of the robot in forward chaining together with results of previous rules and events resulting from these rules.

step 5: Find the appropriate rules applied in Knowledge Base (KB)
IF an existent rule is placed in K) $THEN$ apply the automated robot rule, $ELSE$ a new rule from an expert will be added to the KB

All of steps can be repeated when a robot completes its action(s) in the multiple decision-making objectives.

5. Evaluation

In this section we set out an evaluation of the proposed approach, the results are considered in Section 6.

5.1. Robot case study using hedge algebras with multiple decision-making objectives

As identified in various decision problems related to mobile robotics, the operating robot identifies targets to identify tasks engaged in the multiple decision-making objectives. $(Q_j(X))$ is the objective function indicated for multiple objectives updated in the robot knowledge-base. For example, the objective function aims to maximise objectives to the (5) following objectives:

1. $(Q(1))$: the robot traverses the operating space visiting all the nodes;
2. $(Q(2))$: the robot must complete its traverse of all the nodes in the operating space (i.e., identify if the nodes(cells) are: (a) clear, (b) are occupied by an obstacle(s), or (c) are bounded by walls);
3. $(Q(3))$: the robot must complete its traverse over the operating space without repeating or overlapping paths (i.e. , to enable the identification of the optimal coverage path);
4. $(Q(4))$: the robot must avoid all static and dynamic (moving) moving obstacles;
5. $(Q(5))$: the robot will find the 'optimal path' including the uncertainties in a dynamic operating space with its simple motion trajectories (e.g., straight lines or circles).

A decision maker can instruct an on-line robot about automatic selection of the strategy in multiple decision-making objectives as follows: S_1 (Cleaning function), S_2 (Cleaning and picking up garbage), S_3 (Cleaning while avoiding objects), S_4 (intelligent multiple making decision), and S_5 (heavy clearing). For example, the value $(Q_j(X))$ is determined using the linguistic variables: *high*, *low*, *very hight*, *very low*, *little high*, *little low* , *possible high*, ... and the quantitative semantic value could be: $(\mu\,(high) = 0.65.\ \mu\,(low) = 0.35.\ \mu\,(very\,low) = 0.12.\ \mu\,(very\,high) = 0.85.\ )$. The values for the opinions of experts related to the value of the objective function is shown in Table 1.

Table 1. Testimonials of experts on the objective function

	Q_1	Q_2	Q_3	Q_4
S_1	very high	very low	little very low	low
S_2	low	very low	high	little low
S_3	very low	little very low	little high	low
S_4	little high	little little high	little low	little low
S_5	high	very high	little very high	very high

The relative degree of importance of the objective function corresponding to the means of rescue is shown in Table 2.

Considering hedge algebras we may observe the following semantic properties:

$$AH_{Muc_{D}o_{D}ap_{U}ng} = (T(X), G, H, \leq)$$
$$G = \{low, high\},\ fm\,(low) = 0.5,\ fm\,(high) = 0.75$$
$$H^{+} = \{very\} = \{h_2\},\ q = 1$$

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

Table 2. Testimonials of experts on the importance of the media to participate in rescue

	W_1	W_2	W_3	W_4
S_1	imp	imp	unimp	very very imp
S_2	unimp	unimp	imp	unimp
S_3	unimp	unimp	unimp	unimp
S_4	little imp	little imp	very unimp	little imp
S_5	little imp	little imp	very imp	very very imp

$H^- = (little) = \{h_1\},\ p = 1$
$\theta = 0.5\ and\ \alpha = 0.5$

- $\alpha = \sum_{i=1}^{p} \mu(h_1)\ \mu(little) = 0.5$
- $\beta = \sum_{i=p+1}^{p=q} \mu(h_i) = \mu(h_i) = \mu(very) = (1-\alpha) = (1-0.5) = 0.5$
- $\alpha = \beta \rightarrow (w(h_j x)) = \frac{1}{2}\left[1 + Sign(h_j x)\ Sign(h_p h_j x)\ (\beta - \alpha)\right] = 0.5,\ (\forall h_j \in H)$
- $fm(low) = \theta = 0.5$

  $fm(very\ low) = (\mu(very) * fm(low)) = (0.5\,x\,0.5) = 0.25$

  $fm(little\,low) = (\mu(little) * fm(low) = (0.5\,x\,0.5) = 0.25)$
- $fm(high) = (1 - fm(high)) = (1 - 0.5) = 0.5$

  $fm(very\,high) = (\mu(very) * fm(high)) = (0.5\,x\,0.5) = 0.5$

  $fm(very\,high) = (\mu(little) * fm(high)) = (0.5\,x\,0.5) = 0.5$
- $\nu(W) = \nu(\theta) = 0.5$

  $\nu(low) = (\theta - \alpha fm(low)) = (0.5 - (0.5\,x\,0.5)) = 0.25$

  $\nu(high) = (\theta + \alpha fm(high)) = (0.5 + (0.5\,x\,0.5)) = 0.75$
- $\nu(very\ low) = \nu(low) + Sign(very\ low) * [fm(very\ low) - 0.5fm(very\ low)] = 0.25 + (-1) * (0.25 - (0.5 * 0.25)) = 0.125$
- $\nu(little\ low) = \nu(low) + Sign(little\ low) * [fm(little\ low) - 0.5fm(little\ low)] = 0.25 + (+1) * (0.25 - (0.5 * 0.25)) = 0.375$
- $\nu(very\ high) = \nu(high) + Sign(very\ high) * [fm(very\ high) - 0.5fm(very\ high)] = 0.75 + (+1) * (0.5 * 0.5 * 0.5) = 0.875$
- $\nu(little\ high) = \nu(high) + Sign(little\ high) * [fm(little\ high) - 0.5fm(little\ high)] = 0.75 + (-1) * (0.5 * 0.5 * 0.5) = 0.625$
- $\nu(very\ very\ low) =$
  $\nu(very\ low) + Sign(little\ very\ low) * [fm(little\ very\ low) - 0.5fm(little\ very\ low)] =$
  $0.125 + (+1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.0625$
- $\nu(little\ very\ low) =$
  $\nu(very\ low) + Sign(very\ very\ low) * [fm(very\ very\ low) - 0.5fm(very\ very\ low)] =$
  $0.125 + (+1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.1875$
- $\nu(very\ little\ low) =$
  $\nu(little\ low) + Sign(very\ very\ little\ low) * [fm(very\ little\ low) - 0.5fm(very\ little\ low)] =$
  $0.375 + (-1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.3125$
- $\nu(very\ little\ low) =$
  $\nu(little\ low) + Sign(little\ little\ low) * [fm(little\ little\ low) - 0.5fm(little\ little\ low)] =$
  $0.375 + (+1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.4375$
- $\nu(little\ little\ high) =$
  $\nu(little\ high) + Sign(little\ little\ high) * [fm(little\ little\ high) + 0.5fm(little\ little\ high)] =$
  $0.625 + (-1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.5625$

 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

- $\nu\,(very\ little\ high) =$
  $\nu\,(little\ high) + Sign\,(very\ little\ high) * [fm\,(very\ little\ high) - 0.5fm\,(very\ little\ high)] =$
  $0.625 + (+1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.6875$
- $\nu\,(little\ very\ high) =$
  $\nu\,(very\ high) + Sign\,(little\ very\ high) * [fm\,(little\ very\ high) - 0.5fm\,(little\ very\ high)] =$
  $0.875 + (-1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.8125$
- $\nu\,(very\ very\ high) =$
  $\nu\,(very\ high) + Sign\,(very\ very\ high) * [fm\,(very\ very\ high) - 0.5fm\,(very\ very\ high)] =$
  $0.875 + (+1) * (0.5 * 0.5 * 0.5 * 0.5) = 0.9375$

Testimonials of specialist functions targeted are shown in Table 3.

Table 3. Testimonials of experts on the objective function

	Q_1	Q_2	Q_3	Q_4
S_1	0.875	0.125	0.1875	0.25
S_2	0.25	0.125	0.75	0.375
S_3	0.125	0.1875	0.625	0.25
S_4	0.625	0.6875	0.375	0.375
S_5	0.75	0.1375	0.1125	0.875

Moreover we may observe the following relationships relating to hedge algebras:

1. $AH_{Su_{Quan_Trong}} = (T\,(X)\,,\ G,\ H,\ \leq)$
2. $G = \{unImp,\ imp\}\ fm\,(unImp) = 0.4,\ fm\,(imp) = 0.6$
3. $H^+ = \{very\} = \{h_2\}\,,\ q = 1,\ \mu\,(very) = 0.65$

   $H^+ = \{little\} = \{h_1\}\,,\ q = 1,\ \mu\,(little) = 0.35$
4. $\theta = W = 0.4\ and\ \alpha = 0.35$

Similarly, we obtain a quantitative semantic value for some value in the linguistic variable as shown in Table 4.

Table 4. Table 4. Quantitative value of the variable semantic language

μ (very very unimportant) = 0.10985	μ (very unimportant) = 0.169
μ (little very unimportant) = 0.20085	μ (unimportant) = 0.26
μ (little little unimportant) = 0.29185	μ (little unimportant) = 0.309
μ (very little unimportant) = 0.34085	μ (very little important) = 0.488725
μ (little important) = 0.5365	μ (little little important) = 0.562225
μ (important) = 0.61	μ (little very important) = 0.698725
μ (very important) = 0.7465	μ (very very important) = 0.835225

The degree of importance of the objective function corresponding to the rescue means is shown in Table 5.

Table 5. The weighting of the objective function with the important means of rescue

	W_1	W_2	W_4	W_4
S_1	0.61	0.61	0.26	0.835225
S_2	0.26	0.26	0.61	0.26
S_3	0.26	0.26	0.26	0.26
S_4	0.5365	0.5365	0.169	0.5365
S_5	0.5365	0.5365	0.7465	0.15225

Using the algorithms the $Hedge_DSS$ calculates which option is selected and the order of priority schemes:

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

- $Hedge_D SS = \frac{Min}{x} \sum_j w_j.Q_j\,(X)$
- $\sum_j w_j \,x\, Q_1 = ((0,875\,x\,0.61) + (0,125\,x\,0.61) + (0.1875\,x\,0.26) + (0.25\,x\,0.835225)) = 0.86756$
- $\sum_j w_j \,x\, Q_2 = ((0.25\,x\,0.26) + (0,125,x,0.26) + (0.75\,x\,0.61) + (0,375\,x\,0.26)) = 0.6525$
- $\sum_j w_j \,x\, Q_3 = ((0,125\,x\,0.26) + (0.1875\,x\,0.26) + (0,625\,x\,0.26) + (0.25\,x\,0.26)) = 0.30875$
- $\sum_j w_j \,x\, Q_4 = ((0,625\,z\,0.5365) + (0.6875\,x\,0.5365) + (0,375\,z\,0,169) + (0,375\,x\,0.5365)) = 0.96872$
- $\sum_j w_j \,x\, Q_4 = ((0.75\,x\,0.5365) + (0.1375\,x\,0.5365) + (0.1125\,x\,0.7465) + (0,875\,x\,0.15225)) = 0.6876$

Apply the STC algorithm:

- $\frac{Min}{x} \sum_j w_j.Q_j\,(X) = Mim\,[0.86756,\ 0.6525,\ 0.3087,\ 0.9687,\ 0.6876] = 0.3087$

After applying the proposed model as $Robot - Hedge_{DSS} operator$, decisions will find their way to each vehicle based on priority. According to the calculation results for the above examples the order of cars will be as follows: $S_4 > S_1 > S_5, > S_2 > S_3$.

Figure 4. The Cleaning on-line robot

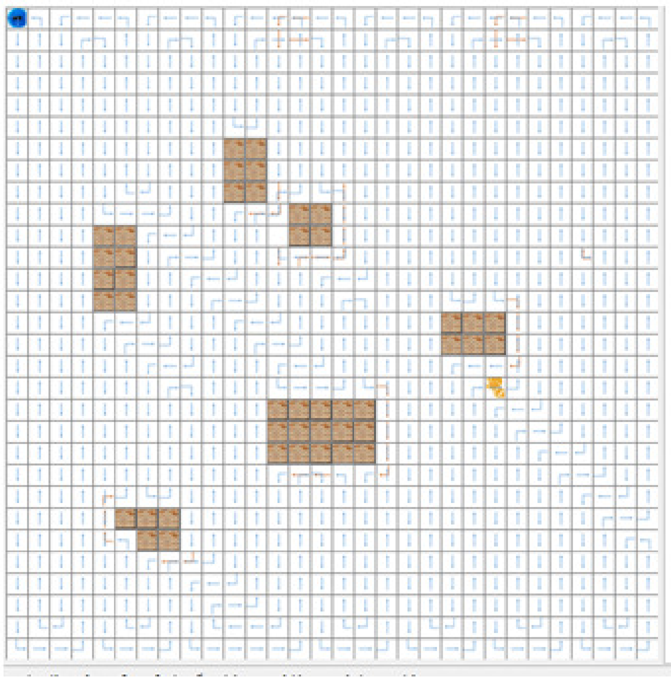

Figure 5. The Cleaning robot using basic cleaning function

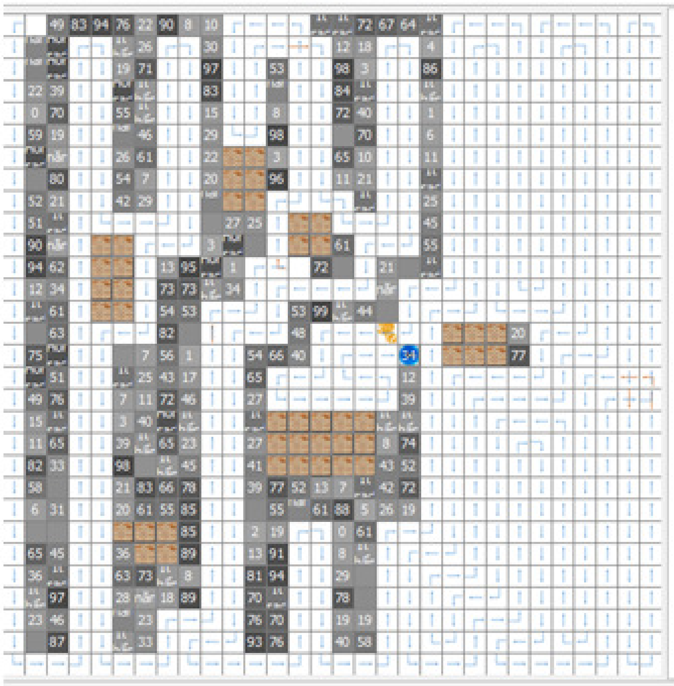

Figure 6. The Cleaning robot in operation using multiple decision making

6. Experimental results and evaluation

In this section we present the experimental results for our proposed approach with a comparative analysis which compares the performance (the repetition rate in covering the defined operating area) of our approach with alternative algorithms. The robot is shown in Figure 4 with the interface (the dynamic environment) of the algorithms as shown in Figures 5, 6, and 7 which show the results for the robot in traversing the dynamic environment based on multiple decision-making objectives.

6.1. The Experimental results

To evaluate our proposed CPP approach (the proposed CPP is the development of the original SCT algorithm) we have conducted a comparative analysis which compares the performance of the SSTC approach with alternative path planning algorithms. The alternative algorithms evaluated are: BFS and Internal Spiral Search (ISS), and U-turn A^* Path Planning (UAPP) [27]. In further testing, we have implemented the ISS algorithm as an inner spiral algorithm where a robot traverses this environment area in a certain direction [27]. The U-turn A^* Path Planning (UAPP) algorithm is a complete path planning coverage approach which uses the A^* algorithm as a heuristic in the U-turn search algorithm. Our proposed model is predicated on the same conditions and mapping with respect to the range of cell numbering (80-250 cells).

The interface for the algorithms has been tested as shown in Figures 5, 6, and 7. Figure 5 shows the experimental interface, Figure 6 shows the path for the proposed model where there are no moving obstacles, and Figure 7 shows the path for the proposed model in a dynamic operating space where there are moving obstacles.

6.2. A Comparison of the Repetition rate for the algorithms evaluated

To evaluate the proposed CPP model we have evaluated the repetition rate in terms of the ability to avoid repetition in covering the defined operating area. Table 6 summarises the complete CPP performance in terms of the repetition rate in a comparative analysis in various environments including: regular obstacles, irregular obstacles, multiple obstacles and multiple irregular obstacles.

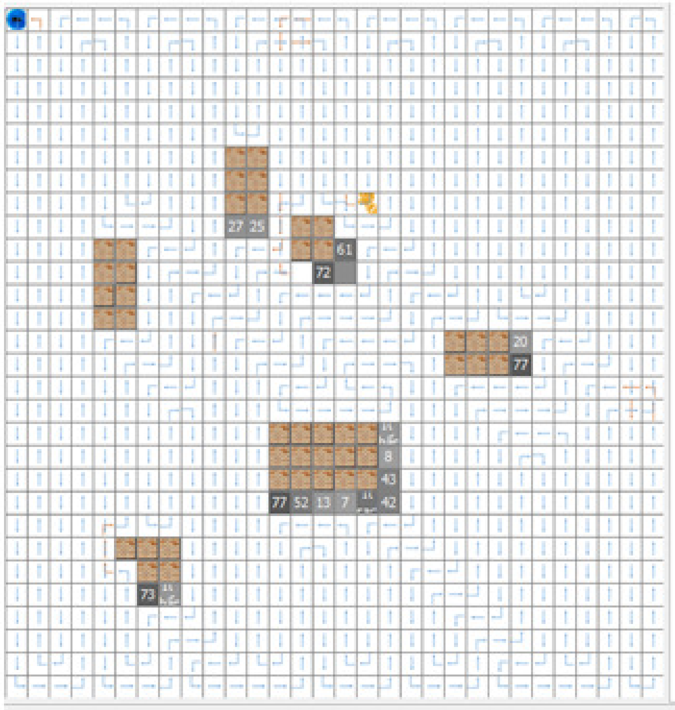

Figure 7. The Cleaning robot operating in heavy cleaning mode

Table 6. The repetition rate in a simulation evaluating alternative algorithms considered in a comparative analysis under differing environments

Methods	Obstacles				Multiple Decision Making Objectives
	Regular (%)	Irregular (%)	Multiple Regular (%)	Multiple Irregular (%)	Average (%)
BFS	4.00	3.10	36.50	32.50	50
ISS	7.00	20.50	19.50	26.10	53
UAPP	5.00	5.40	8.85	14.40	67
CPP	**0.00**	**2.20**	**2.00**	**7.30**	**96**

As shown in Table 6, the simulation results for the proposed CPP model show that it achieves a higher coverage rate with low repetition rate as compared to the alternative algorithms evaluated. The proposed approach has achieved complete coverage of the operating space with a low repetitive coverage rate.

In case studies of robots in various environments (regular, irregular, multiple regular, and multiple irregular obstacles), the repetition rate for the proposed CPP model demonstrates a significant performance improvement over the BFS, ISS and UAPP methods with respect to simple regular and irregular obstacle environments. In complex regular and irregular obstacle environments, the repetition rate of the CPP model is lower than achieved for the BFS, ISS and UAPP algorithms.

6.2.1. Comparison of Repetition rate and duration in robot coverage path planning with moving obstacles

In the experimental testing we have conducted a comparative analysis of the proposed CPP model with the other traditional methods considered, these methods were: BFS, ISS, and UAPP methods. The evaluation compared: (a) the duration, awareness, and ability [of the robot] to cover both static

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at *Machines* **2018**, *6*, 46; doi:10.3390/machines6040046

and dynamic environments, and (b) the repetition rate where a robot faces obstacles in uncertain and dynamic operating environments. The testing evaluated the operating environment with regular, irregular, multiple regular, and multiple irregular obstacles. The experimental testing is based on an operating environment with robot cell numbers in the range (80-250), the results derived from the experimental testing are summarised in Figures 5, 6, and 7 and Tables 6, 7, and 8.

Table 7. A comparative analysis of the duration time to traverse the operational environment

Methods	Duration (seconds) / Obstacles				
	Regular	**Irregular**	**Multiple Regular**	**Multiple Irregular**	**Average**
BFS	134	154	150	144	140
ISS	115	135	130	125	120
UAPP	95	115	95	110	100
CPP	**66**	**78**	**79**	**74**	**82**

Table 8. A comparative analysis of the repetition rate in traversing the operational environment

Methods	Repetition Rate (%) \Obstacles				Repetition Rate (%) / Multiple Decision Making
	Regular (%)	**Irregular (%)**	**Multiple Regular (%)**	**Multiple Irregular (%)**	**Average %)**
BFS	14	29	38.5	38	40
ISS	16	25	29.5	32	35
UAPP	8	12	15	25	29
CPP	**3**	**4**	**3**	**11.3**	**13.2**

From Tables 6, 7, and 8 it may be seen that the repetition rate (for a robot to traverse an operating space – effectively the search space) for our CPP model under all operating environments massively outperforms the alternative methods considered. The improvement in the performance is evidenced by the ability of the CPP method to achieve complete coverage of the operational environment with a very low repetitive coverage rate in the range 3% to 11.3% with an average repetition rate in multiple decision-making operation of 13.2%. In the general case, our proposed CPP method provides the shortest duration with the lowest repetition rate. The experimental results demonstrate the effectiveness of the proposed SSTC model in terms of the repetition and time travelled in uncertain environments where the robot will encounter both static and moving obstacles. The results for the CPP model are clearly superior to the results for the BFS, ISS, and UAPP methods

7. Discussion

I the developing field of robotics the development of robotic systems modelled on human cognitive functions is gaining significant traction. Such research is exemplified by the ground breaking research led by Prof Sheila Nirenberg at the Nirenberg lab in the Department of Physiology and Biophysics at the Weill Medical College of Cornell University, USA. The research carried out at the Nirenberg Lab combines medical and computer science research and applies this work to both human medical treatments and robotics as exemplified in the research documented in [28] [29].

In this paper we have considered CPP and introduced our novel robot control approach designed to enable effective and efficient path planning implemented using a linguistic approach based on semantics and hedge algebras [30]. The proposed method has been evaluated and we have

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at Machines 2018, 6, 46; doi:10.3390/machines6040046

demonstrated using a case study that the proposed method provides and effective basis upon which CPP in a dynamic search space may be realised.

7.1. The Concept of Self

In discussing the philosophy of the mind and cognitive science, Gallagher introduces the concept of *self* which includes *self-awareness*. A detailed discussion on this topic is beyond the scope of this paper, a detailed exposition, for a discussion on the topic see [31]. In summary, there are two concepts of self: the *minimal* self ("a self devoid of temporal extension") and the *narrative* self (which "involves personal identity and continuity across time"). The twin concepts of *self* illustrate how the philosophical approach can inform cognitive science and suggests that a two-way collaboration [between neuroscience and computer science] may lead to a more fully-developed account of self and awareness in entities (e.g., humanoid robotic systems as discussed in Section 7.2) and computer systems with potential applications in machine cognition, machine consciousness and machine self-awareness. The concept of *self* may be viewed as an entities *internalized* view of the world developed over time based on the interactive experience of their *externalized* world [32].

Going further, we must consider the *stimuli* that prompt a reactive response. There are two types of stimuli: (i) *external* stimuli (reactive situations that confront an entiy in their interaction with their environment) and (ii) *internal* stimuli (internally-generated actions that the entity initiates). In practice, entities (which include both humans and intelligent robotic systems) interact with their 'world' and learned experience gained from their external environment 'feeds' into the *internalized* self, which in turn influences the way entities interact with their world. This process can be viewed as a continuous cognitive information processing feedback loop [32]. The aim of machine cognition research is to implement (at least on a very primitive level) in computerised systems a representation of a human dynamic cognitive model. For humans, internal cognitive models form a significant component in response to stimuli [33] [15]. Such a component equally applies to intelligent robotic systems implementing internal cognitive models.

The aim of intelligent systems (including intelligent robotic systems) is to achieve set goals, this aim may be reflected in meeting defined goals for entities in dynamic environments as introduced in this paper. Intelligent must be *context-aware* and must be adaptive to dynamic environments [34] and, hence, must adopt different forms when the environments are correspondingly different [35]. Such adaptive systems may be described as "*artificial*" [35] for, as environments change, systems must change to match the dynamic *states* and thus *mirror* the new situation [34,36]. Machine cognition is designed to incorporate cognitive functions and processes (on a primitive level as compared to human cognition) in highly autonomous machines (such as robotic systems) and intelligent entities.

7.2. Machine Cognition

Human cognition creates a psychophysiological process triggered spontaneously by the conscious and subconscious sense of an object [37] [38]. Given the traction in intelligent systems (including robotic systems) there exists the potential to model cognitive response in intelligent machines and computer systems. Due to the complexity in human cognitive processing when viewed from the perspective of physiology and psychophysiology machine cognition represents a significant challenge and realising machine cognition remains an open research question.

Prakash Mondal considers machine cognition and poses the question: "Does computation reveal machine cognition?" [39]. He argues that the nature of machine cognition has been shrouded in "incomprehensibility" and that "human cognition is still faintly understood". Moreover, he goes further in arguing that machine cognition is far less understood than human cognition despite the current knowledge relating to computer architectures and systems. Human interpretation [of computation] is required, where it becomes a type of "*semiotic causation*" (SC), which "*gives meaning to computation*" [39]. The research documented in this paper has a correlation with semiotics and SC in that humans recognise and communicate using linguistics which are important in semiotics [40] [41]. Intelligent

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 August 2018 doi:10.20944/preprints201808.0125.v1

Peer-reviewed version available at *Machines* **2018**, *6*, 46; doi:10.3390/machines6040046

systems (such as robotic systems) may leverage semantics and semiotics to realise machine cognition that replicates (at least on a primitive level) human cognitive processes.

Computational entities will include intelligent agents and humanoid robotic systems (which include both *physical* and *computational* entities). Intelligent robotic systems (physical and computational) may be viewed as entities which will embody: (i) the concept of *self*, (ii) *self-awareness*, (iii) awareness of their 'world'. However, such systems and agents must adapt dynamically to the changing environment based of learning as modelled in the 'feedback-loop' [32].

7.3. Future Directions for Research

In considering the research documented in this paper, while many issues relating to semantics and the use of linguistic methods [as they relate to CPP] have been explored and resolved there remain open research questions relating to the operational capabilities of intelligent entities in dynamic operating environments.

The posited approach presented in this paper has been shown provide an effective basis for autonomous robot control based on *context-awareness* [34] and *self-awareness* [32]. However, there may be use-cases where it may be desirable for a robot to move directly from a specified point to another specified point [within a defined operational environment] where an object is located (for any number of reasons). In such a use case, the proposed approach may be extended to identify the most direct route while retaining the capability to avoid dynamic (independently mobile) obstacles.

We propose a number of interesting directions for research. Extending the proposed rule-based linguistic approach using semantics with *kansei* engineering with and hedge algebras forms an interesting approach. A further potentially profitable (in computing terms) lies in the use of semiotics [40] (to recognise the type and nature of obstacles) and in use-case is where multiple robots may operate collaboratively using for example 'forward chaining' (an awareness of their environment and other robots operating in the same dynamic environment). For example, in a large search area multiple robots may be deployed to investigate a defined area; in such a use-case efficient search requires both CPP for each robot while avoiding duplication in the search activity.

Integrating *kansie* engineering with semiotics into the proposed approach presented in this paper forms the basis for future research.

8. Concluding Observations

In this paper, we have considered the CPP problem and we have presented our novel CPP robot control approach designed to enable effective and efficient CPP. To evaluate out proposed approach we have presented an implementation based on a cleaning robot traversing a dynamic operating space characterised by both static (non-moving) and dynamic (independently moving) obstacles. In operation, the robot has shown the capability to map the operating space (thereby remembering static objects and also capturing the location of dynamic objects. Our novel approach has demonstrated the capability to traverse an operating space efficiently without repetition or overlapping of coverage paths. The posited approach provides and interesting direction for research into intelligent autonomous robotic control.

Acknowledgements

This research is funded by Vietnam Ministry of Education and Training under grant number B2015-01-91

References

1. Bayat, F.; Najafinia, S.; Aliyari, M. Mobile robots path planning: Electrostatic potential field approach. *Expert Systems with Applications* **2018**, *100*, 68 – 78. doi:https://doi.org/10.1016/j.eswa.2018.01.050.
2. Galceran, E.; Carreras, M. A survey on coverage path planning for robotics. *Robotics and Autonomous Systems* **2013**, *61*, 1258 – 1276. doi:https://doi.org/10.1016/j.robot.2013.09.004.
3. Chen, X.; Zhang, Y.; Xie, J.; Du, P.; Chen, L. Robot needle-punching path planning for complex surface preforms. *Robotics and Computer-Integrated Manufacturing* **2018**, *52*, 24 – 34. doi:https://doi.org/10.1016/j.rcim.2018.02.004.
4. Mac, T.T.; Copot, C.; Tran, D.T.; Keyser, R.D. Heuristic approaches in robot path planning: A survey. *Robotics and Autonomous Systems* **2016**, *86*, 13 – 28. doi:https://doi.org/10.1016/j.robot.2016.08.001.
5. Mohanan, M.; Salgoankar, A. A survey of robotic motion planning in dynamic environments. *Robotics and Autonomous Systems* **2018**, *100*, 171 – 185. doi:https://doi.org/10.1016/j.robot.2017.10.011", url = "http://www.sciencedirect.com/science/article/pii/S0921889017300313.
6. Acar, E.U.; Choset, H.; Zhang, Y.; Schervish, M. Path planning for robotic demining: Robust sensor-based coverage of unstructured environments and probabilistic methods. *The International journal of robotics research* **2003**, *22*, 441–466.
7. Han, J.; Seo, Y. Mobile robot path planning with surrounding point set and path improvement. *Applied Soft Computing* **2017**, *57*, 35 – 47. doi:https://doi.org/10.1016/j.asoc.2017.03.035.
8. Jin, L.; Li, S.; Yu, J.; He, J. Robot manipulator control using neural networks: A survey. *Neurocomputing* **2018**, *285*, 23 – 34. doi:https://doi.org/10.1016/j.neucom.2018.01.002.
9. Martínez-Tenor, A.; Fernández-Madrigal, J.A.; Cruz-Martín, A.; González-Jiménez, J. Towards a common implementation of reinforcement learning for multiple robotic tasks. *Expert Systems with Applications* **2018**, *100*, 246 – 259. doi:https://doi.org/10.1016/j.eswa.2017.11.011.
10. Agostini, A.; Torras, C.; Wörgötter, F. Efficient interactive decision-making framework for robotic applications. *Artificial Intelligence* **2017**, *247*, 187 – 212. Special Issue on AI and Robotics, doi:https://doi.org/10.1016/j.artint.2015.04.004.
11. Leottau, D.L.; del Solar, J.R.; Babuška, R. Decentralized Reinforcement Learning of Robot Behaviors. *Artificial Intelligence* **2018**, *256*, 130 – 159. doi:https://doi.org/10.1016/j.artint.2017.12.001.
12. Karapetyan, N.; Benson, K.; McKinney, C.; Taslakian, P.; Rekleitis, I. Efficient multi-robot coverage of a known environment. Intelligent Robots and Systems (IROS), 2017 IEEE/RSJ International Conference on. IEEE, 2017, pp. 1846–1852.
13. Muñoz, P.; R-Moreno, M.D.; Barrero, D.F. Unified framework for path-planning and task-planning for autonomous robots. *Robotics and Autonomous Systems* **2016**, *82*, 1 – 14. doi:https://doi.org/10.1016/j.robot.2016.04.010.
14. Patle, B.; Parhi, D.; Jagadeesh, A.; Kashyap, S.K. Matrix-Binary Codes based Genetic Algorithm for path planning of mobile robot. *Computers & Electrical Engineering* **2018**, *67*, 708 – 728. doi:https://doi.org/10.1016/j.compeleceng.2017.12.011.
15. Moore, P.T.; Pham, H.V. On Context and the Open World Assumption. The 29th IEEE International Conference on Advanced Information Networking and Applications (AINA-2015); IEEE, IEEE: Gwangju, Korea, 2015; pp. 387–392. doi:10.1109/WAINA.2015.7.
16. Brooks, R.A. Intelligence without representation. *Artificial Intelligence* **1991**, *47*, 139–159.
17. Fakoor, M.; Kosari, A.; Jafarzadeh, M. Humanoid robot path planning with fuzzy Markov decision processes. *Journal of Applied Research and Technology* **2016**, *14*, 300 – 310. doi:https://doi.org/10.1016/j.jart.2016.06.006.
18. Mac, T.T.; Copot, C.; Tran, D.T.; Keyser, R.D. A hierarchical global path planning approach for mobile robots based on multi-objective particle swarm optimization. *Applied Soft Computing* **2017**, *59*, 68 – 76. doi:https://doi.org/10.1016/j.asoc.2017.05.012.
19. Palacios-Gasós, J.M.; Talebpour, Z.; Montijano, E.; Sagüés, C.; Martinoli, A. Optimal path planning and coverage control for multi-robot persistent coverage in environments with obstacles. Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE, 2017, pp. 1321–1327.

Peer-reviewed version available at *Machines* **2018**, *6*, 46; doi:10.3390/machines6040046

20. Bouzid, Y.; Bestaoui, Y.; Siguerdidjane, H. Quadrotor-UAV optimal coverage path planning in cluttered environment with a limited onboard energy. Intelligent Robots and Systems (IROS), 2017 IEEE/RSJ International Conference on. IEEE, 2017, pp. 979–984.
21. Li, D.; Wang, X.; Sun, T. Energy-optimal coverage path planning on topographic map for environment survey with unmanned aerial vehicles. *Electronics Letters* **2016**, *52*, 699–701.
22. Wang, J.; Chen, J.; Cheng, S.; Xie, Y. Double Heuristic Optimization Based on Hierarchical Partitioning for Coverage Path Planning of Robot Mowers. Computational Intelligence and Security (CIS), 2016 12th International Conference on. IEEE, 2016, pp. 186–189.
23. Chen, K.; Liu, Y. Optimal complete coverage planning of wall-climbing robot using improved biologically inspired neural network. Real-time Computing and Robotics (RCAR), 2017 IEEE International Conference on. IEEE, 2017, pp. 587–592.
24. Lin, Y.Y.; Ni, C.C.; Lei, N.; Gu, X.D.; Gao, J. Robot Coverage Path planning for general surfaces using quadratic differentials. Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE, 2017, pp. 5005–5011.
25. Ho, N.C.; Wechler, W. Hedge algebras: an algebraic approach to structure of sets of linguistic truth values. *Fuzzy sets and systems* **1990**, *35*, 281–293.
26. Ho, N.C.; Long, N.V. Fuzziness measure on complete hedge algebras and quantifying semantics of terms in linear hedge algebras. *Fuzzy Sets and Systems* **2007**, *158*, 452 – 471. doi:https://doi.org/10.1016/j.fss.2006.10.023.
27. Cai, Z.; Li, S.; Gan, Y.; Zhang, R.; Zhang, Q. Research on complete coverage path planning algorithms based on a* algorithms. *The Open Cybernetics Systemics Journal* **2014**, *8*, 418–426.
28. Nirenberg, S.; Carcieri, S.M.; Jacobs, A.L.; Latham, P.E. Retinal ganglion cells act largely as independent encoders. *Nature* **2001**, *411*, 698. doi:https://doi.org/10.1038/35079612.
29. Nirenberg, S.; Pandarinath, C. Retinal prosthetic strategy with the capacity to restore normal vision. *Proceedings of the National Academy of Sciences* **2012**, *109*, 15012–15017. Suplementary supporting material is available on-line at: www.pnas.org/lookup/suppl/doi:10.1073/pnas.1207035109/-/DCSupplemental, doi:https://doi.org/10.1073/pnas.1207035109.
30. Pham, H.V.; Moore, P.; Tran, K.D. Context Matching with Reasoning and Decision Support using Hedge Algebra with Kansei Evaluation. Proc of the fifth symposium on Information and Communication Technology (SoICT 2014); ACM, ACM, New York, NY, USA: Hanoi, Vietnam, 2014; pp. 202–210. doi:10.1145/2676585.2676598.
31. Gallagher, S. Philosophical conceptions of the self: implications for cognitive science. *Trends in cognitive sciences* **2000**, *4*, 14–21.
32. Moore, P. Do We Understand the Relationship between Affective Computing, Emotion and Context-Awareness? *Machines* **2017**, *5*. doi:10.3390/machines5030016.
33. Moore, P.; Xhafa, F.; Barolli, L. Semantic valence modeling: Emotion recognition and affective states in context-aware systems. 28th International Conference on Advanced Information Networking and Applications Workshops (WAINA 2014); IEEE, IEEE: Victoria, BC, Canada, 2014; pp. 536–541. doi:10.1109/WAINA.2014.88.
34. Moore, P.; Pham, H.V. Personalization and rule strategies in human-centric data intensive intelligent context-aware systems. *The Knowledge Engineering Review* **2015**, *30*, 140–156. doi:10.1017/S0269888914000265.
35. Simon, H.A. Cognitive science: The newest science of the artificial*. *Cognitive science* **1980**, *4*, 33–46.
36. Simon, H.A. The sciences of the Artificial. *Massachusetts Institute of Technology* **1969**.
37. Koelstra, S.; Muhl, C.; Soleymani, M.; Lee, J.S.; Yazdani, A.; Ebrahimi, T.; Pun, T.; Nijholt, A.; Patras, I. Deap: A database for emotion analysis; using physiological signals. *IEEE Transactions on Affective Computing* **2012**, *3*, 18–31. doi:10.1109/T-AFFC.2011.15.
38. Chen, J.; Hu, B.; Moore, P.; Zhang, X., Ontology-Based Model for Mining User's Emotions on the Wisdom Web. In *Wisdom Web of Things*; Zhong, N.; Ma, J.; Liu, J.; Huang, R.; Tao, X., Eds.; Springer International Publishing: Cham, 2016; Vol. Wisdom Web of Things (W2T), *Web Information Systems Engineering and Internet Technologies*, chapter 6, pp. 121–153. doi:10.1007/978-3-319-44198-6_6.
39. Mondal, P. Does Computation Reveal Machine Cognition? *Biosemiotics* **2014**, *7*, 97–110.
40. Chandler, D. *Semiotics: The Basics*; Psychology Press, 2002.

Peer-reviewed version available at *Machines* **2018**, *6*, 46; doi:10.3390/machines6040046

41. Tanaka-Ishii, K. *Semiotics of programming*; Cambridge University Press, 2010.