Real-Time Co-Operative Decision Making & Control Systems

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***Abstract*—Learning and adaptability (and thus the ability of being co-operative) are important features of decision & control systems. This paper investigates decision making and control concepts that enable human beings and artificial beings to interact and co-operate in real time in a dynamic and reliable way. It examines the aspects of being co-operative and substitutable in the context of: (i) co-operative driving by driverless vehicles; and (ii) computer game play scenarios for collaborative and social interactions.**

Keywords-co-operative systems; decision & control systems

I. INTRODUCTION

Although simple in their definition, Co-operative Decision & Control Systems are difficult to model and analyze, and extremely difficult to build. They are however becoming an increasingly important "solution key" to incredibly numerous applications and do foster trans-disciplinary and multi-disciplinary research efforts towards the development of co-operative systems problem solving techniques.

Normally, co-operative systems consist of multiple agents (decision makers) each representing either biological or an artificial creature (i.e. human being or an artificial being), acting together towards accomplishing mutually agreed objectives [1][1] . In addition, the agents can also try to achieve their local objectives, simultaneously with their effort in achieving the common (i.e. shared) goals.

Examples of co-operative systems are numerous.

They can be: students and teachers in the classroom, employees at their workplace, drivers and pedestrians on the roads, robots in the factory, people at a party, aircraft in the sky, and robots in search-and-rescue operations. However, they can also be: unmanned aircraft in military surveillance and attack missions, or robots on the battlefield.

Thus, co-operative systems attract an interest not just from control engineers and scientists but also from biologists, economists, applied mathematicians, computer scientists, many decision theorists, and of course, social and political scientists.

II. CO-OPERATIVE SYSTEMS: AN OVERVIEW

The term Co-operative Systems is an umbrella term for many business, social and research systems ranging from the tools and services that facilitate collaboration to intelligent group decision-making processes. The common trait bringing this all together is collaboration: the ability for agents (human or otherwise) to actively contribute together towards a common goal or outcome.

The following section explores co-operative systems in three broad categories: Facilitation (tools and services), Communication (social ability) and Decision-Making (methods and processes). Many of the co-operative systems mentioned exemplify more than one of the traits of the categories described below.

A. Facilitation

Co-operative environments are based on knowledge, and therefore collaboration shares a strong interdependence with knowledge management [2]. To facilitate this, many tools and technologies have been developed to facilitate inter-human collaboration and the management of group knowledge. In many organizations, tools of this nature can be as simple as an email system, while in others complex knowledge management occurs in conjunction with sophisticated collaborative workflows [3] and integrated collaboration environments [4]. Such co-operative systems however are simply facilitation mechanisms for humans. In the area of human-computer interaction, the discourse theory can however be explored

[1] "It is where the co-operative systems differ from game-theory problems where the actors play the game under, in principle, mutually conflicting (confronting) interests. In the simplest game, a zero-sum matrix game, the gain of one player is the loss of another." [1].

towards designing and implementing intelligent collaborative interfaces to facilitate human-computer interaction [5].

In more sophisticated interactions between business services languages the Web Ontology Language (known as OWL) was used to support interaction in co-operative semantic web systems [6].

Rich Internet Applications (RIAs) are becoming more popular, with large corporations such as Google, Microsoft and Amazon vying for position to become the dominant provider of Rich Internet Applications (RIAs) and services on "The Cloud". A lot of hype surrounds this term, but in essence the cloud simply refers to distributed systems making data and resources available via a network.

Many cloud-based web applications include social and co-operative components. Such an example is Google's Documents (a web-based Word Processor) that includes collaborative editing and communication.

B. Communication

When dealing with collaborative multi-agent systems that do not involve humans, inter-agent communication or social ability [7] is accomplished via structured messages and interfaces [8].

Just as humans, businesses must also effectively communicate. For example, supply chain management involves many businesses. To achieve collaborative integration of such systems, the two main approaches are to mandate standard terminology and protocols or the use of a mediator to facilitate co-operation [9].

The embodiment or representation of a player within a collaborative virtual environment can also be used to convey visual information in much the same way as body language can in direct human interactions [10] but are challenges as virtual communication cannot convey as much meaning to humans as direct interaction [11]. However, effective collaborative communication amongst heterogeneous devices has allowed those without or with limited vision capability to navigate real-world situations [12].

Interestingly, the largest and most common examples of co-operative systems used by people every day are social networks such as Facebook and Twitter. Social Networks have changed the way in which millions of people worldwide communicate these days.

In early 2011, Queensland and Brisbane experienced terrible flooding. During this time, media outlets relied on first-hand information provided by people using Social Networks. At the peak of the crisis, city-based companies had staff working from home. Power was cut to most of the Central Business District (CBD). In many cases, organizations in this situation relied on social networks to relay information to staff.

Smaller groups of friends also shared information about events directly impacting them for the purpose of either coordinating their joint actions or simply letting their friends know they were safe.

C. Decision-Making

It is commonly assumed that the term co-operative system relates to multi-agent based decision situations. However strictly speaking, these decision processes are not conflict free, since the decision makers may not necessarily be of a co-operative attitude. Thus, a multi-agent decision making system does not always operate as a co-operative system. Finally, multi-agent decision making situations are not always aimed at achieving a joint decision as they can also exist as game-like situations where each decision maker is making an independent decision, and very often to the cost of other decision makers.

As problem domains become more complex, with more conflicting goals, hybrid decision models involving more than one form of decision-making technique become more important [13].

III. Plural Rationality in Multi-agent Decision Situations

An analysis of multi-agent decision system requires an understanding of various plural rationality concepts.

Typically, a plural rationality is of relevance not just to the biological multi-agent decision making situations (i.e. a decision making system whose actors are human beings) but also to the artificial. That is, multi-agent intelligent machine-based decision making systems.

The central issue to all multi-agent based decision making situations is not in the different perceptions of rationality [14][2] among the decision makers but rather, in their willingness to recognize these differences, learn about them and find a way to negotiate. If so, then the abilities to analyze, learn, negotiate and undertake a rational action appear as the immanent features of a successful co-operative system. Here, a multi-agent based co-operative system is understood as a mental model of the reality regardless of whether it consists entirely of human decision makers, intelligent machines, or both.

Many decision theorists tried to conceptually distinct various schools of thought. Instead of presenting each of them separately,[3] a framework for plural rationality and interactive decision processes, as pioneered in [14], will be present here since their quasi-satisficing decision making framework "… can also be used towards understanding of conflict escalation processes and thus help us to prevent escalation of mediation and negotiation".

The quasi-satisficing decision making framework [15][4] has opened an avenue towards a synthesis of several rational

[2] "A rationality is a conceptual framework for perceiving what constitutes rational action. A rational decision does not have to be based on all the available information, nor does it have to be optimal. It should only take into account the possible consequences of the decision and be intended not to be detrimental to the interests of the decision maker". [14]

[3] While elaborating on this framework and related theories only those aspects that are of relevance to control systems and their applications will be addressed.

[4] Can be paraphrased as follows: "The decision maker has a tendency towards maximization, but might, for some good reason, lose this tendency towards achieving his adaptively formed aspiration levels, established over the course of a learning process" [15].

decision making frameworks by way of introducing four postulates to capture the essence of: (i) the interactive learning; (ii) the different perception of rationality; (iii) the organizational structure of the decision making process (hierarchies in particular); and (iv) a fair negotiation and mediation.

A goal-led programming [5], derived from the classical, interest-oriented theory of decision making has found its broad application in robotics and mechatronics in a form of goal-seeking behavior. The goal-setting process has turned out to be computationally feasible as long as it is described by a certain cost function value. The fundamental deficiency of this theory: that of a lack of consideration of the determinants of the goal-setting process and a lack of the ability to aggregate plural interests and identify the patterns of interests, has unfortunately also been inherited by researchers and designers of robotic and mechatronic systems[6].

Since different system designers may assign a different pattern of interests, where these interests are typically culturally oriented, a further aggregation of plural, individual interests is no longer available. As a result, robotic/mechatronic devices, if designed based on the principles of a goal-seeking behavior, would no longer be able to accommodate the diversity of the individual end-user needs.[7] Thus, the goal-seeking behavior is not capable of dealing with situations that are perceived to be novel.

Similarly, holistic decision making systems [8] and their equivalents in the robotics/mechatronics arena have appeared to be truly the most effective approach in resolving standard (typical) decision making situations, as the situation analysis does not need to be performed as long as the situation is identified as the known one[9].

The utility theory [10], although being of the strongest mathematical foundation [11], has not found its significant supporters among control scientists and engineers, mainly due to the facts that: (i) maximizing behavior cannot be consistently rational in any non-zero sum multi-agent situations [14]; (ii) the axiom of independence cannot be justified in real life situations; and (iii) value/utility functions are stationary i.e. do not change in time.

[5] Considered here as a typical representative of the hierarchical decision making frameworks

[6] A typical application of a goal-seeking behavior is in robo-soccer game scenarios. However, it is not to say that every robo-soccer game solution is developed as a goal-seeking behavior.

[7] Since meaning and understanding the term a "rational behavior" might be quite different in different cultures, it is not difficult to see that many technical systems are not equally applicable in different cultures and even some end users have difficulties in adjusting themselves to particular technical devices. Instead of having a device able to adjust itself to particular requirements of its end users, often it is left on the end-user to learn and find the way as to how to facilitate and accommodate the device.

[8] Being a typical representative of behavioral theories.

[9] This is why the automated control systems appear to be very efficient in repetitive decision making situations.

[10] Being a typical representative of the normative decision theories.

[11] Originated from Adam Smith's invisible hand concept.

Reference [16] have upstaged the quasi-satisficing decision making framework by introducing a special cardinal utility function[12], namely, an order-consistent achievement function [16][13]. Its beauty comes from the fact that it does not require decision makers to undertake an often tedious, pairwise comparison of the available alternatives and their features. Instead, the function is eliciting the decision maker's adaptively formed, aspiration levels. Thus, this function serves as an approximation to the preferences of the decision maker.

A general form of the order-consistent achievement function can be described as follows:

$$u(y) = \min_{1 \le i \le p} u_i(y_i) \qquad (1)$$

Where,

$u(y)$ – A multi-attribute cardinal utility function

p – A number of the events

u_i – Individual value function

y_i – Individual attribute value

$y_{i,\min} < \bar{y}_i' < y_i < \bar{y}_i'' < y_{i,\max}$

$\bar{y}_i'$ – The attribute value that must be achieved

$\bar{y}_i''$ – Acceptable tolerance, i.e., a positive variation of $\bar{y}_i'$ values, i=1,2…p

Variations and modifications of this class of functions have been used in:

- the development of algorithms for co-operative driving by driverless systems thus enabling driverless vehicles to co-operate and undertake their driving maneuvers in co-operation with each other [17]
- numerous applications of decision support systems and computer assisted iterative decision making processes [18];
- the development of integrated resource planning decision making processes for the electricity industry sector [19], [20]

[12] "Cardinal utility functions are a sounder basis for aggregating attributes than general value functions. Cardinal utility functions are such value functions which preserve, in the probabilistic expectation sense, given preferences between probability distributions of consequences of uncertain decision alternatives under any positively monotonous and linear or affine transformations of attribute assessment scales. Thus, such functions are themselves independent (up to a positively monotone affine scaling transformation) of any positively monotone affine transformation of their arguments, and any function that possesses such independence properties can be interpreted as a cardinal utility function."[16)]

[13] It can also be interpreted as a L-shaped utility function; and the weighted Chebyshev norm.

- computer integrated manufacturing [21] and
- Complex equipment selection tasks [22].

However, in the framework of this paper we are only interested in co-operative decision making & control algorithms in the context of real-time applications.

IV. Learning And Control

The essence of the power of the feedback control system is in its ability to provide decision makers with an opportunity to learn from outcomes of their actions. Thus, critical to control systems and co-operative systems in general, is their ability to learn over the course of the decision making process.

Thus, an interaction with its surrounding environment is the main feature that a control system needs to exhibit if it is to sustain [23].

Reference [1] was, if not the very first one, then certainly one of the originators of the Learning and Adaptive Control System Concept. Their work on "learning, self-learning and adaptation in automatic systems", initially published mainly in Russian, paved the way to both theoretical research and practical approaches to the design of engineering systems that exhibit learning and adaptation abilities.

Normally, the exact mathematical model of the object to be controlled is not known in advance, and we are often not able to experimentally determine it either [23]. So, as in [1], it is postulated that we should be able to cope with such uncertainty as long as we are able to learn about the object over the course of its control as well as adapt to the object and its dynamics based on information that will be obtained during that process. In doing all of this, our actions are aimed at achieving the best possible operational performance of the system. Thus, we try to achieve optimal performance of the controlled system, not necessarily immediately after imposing our action upon the system but rather, during the process of our learning about the object and our interactions with it. Consequently, learning and adaptation are aimed at achieving the optimum of the system performance, relative to the information obtained. Thus, an extremum seeking process no longer requires an analytical and formal description of the conditions of the problem [1].[14] .

However, to be able to judge whether an optimum is indeed achieved over the process of learning and adaptation[15], one must be familiar with the problem of optimality itself and with the algorithms needed for solving them. This is because an extremum seeking process is often a sequential (multistage) process of defining: (i) the goal and its criteria of optimality; (ii) mutually exclusive constraints; and (iii) the methods ensuring that the criteria of optimality will reach their extremum by satisfying these constraints.

Since an optimal solution can be accepted as an optimal one only from a certain viewpoint (i.e. relative to its constraints) it is very likely that a change in the constraint values will also produce a change in the initially obtained optimal solution value. The dynamics of the decision making process, in particular if occurring under insufficient a priori information (and/or time-varying constraints), can be even further emphasized if more than one decision maker is involved in the decision making process, i.e. more than only one viewpoint becomes relevant.

This is where we are closing the circle since the existence of multiple criteria of optimality and the uncertainty in constraint decision making processes (and their time-varying nature) take us back to our earlier discussion on co-operative control and plural rationality.

In control systems terms, the adaptability is considered as a property of the system to change its parameters (and the structure too, if necessary) in order to change its control actions. In multi-agent decision making terms, the adaptability (i.e. a quasi-satisficing decision making) relates to the most important characteristic of a decision process, that of learning by decision makers and non-stationarity of the decision maker's utility function. That is, the decision makers' willingness to change their utility functions and the initially formed aspiration levels, if that becomes the necessity over the course of their learning process.

Learning and adaptability (and thus the ability of being co-operative) are important features of decision & control systems, regardless of whether the decisions are to be made by human beings, artificial beings, or both. In the remaining section of the paper this issue is taken further by investigating whether human and artificial beings can interact co-operatively and be substitutable in the context of: (i) co-operative driving; and (ii) various computer game play scenarios for collaborative and social interactions.

V. Co-operative System Case Studies

Like man-made engineering systems, the creation of numerous artificial beings has also been driven by human beings' wish to enrich their own resources and improve the quality of their life. Thus artificial beings, having been created by human beings, are empowered to the extent that humans desire: becoming their associates and acting in response to human will.

There is an expectation that artificial beings shall (i) become our partners in the workplace and home, (ii) be able to respond to our requests, and; (iii) not merely recognize our routine, but tune themselves to our specific needs. Thus, the future is in human adaptive robotics and collaborative relationships between human and artificial beings; having robots capable of adapting themselves to the ever changing needs of humans. Since humans use voice, gestures, verbal and facial expressions to convey their opinion, intention and emotions, the robots need to be empowered to recognize and

[14] The determination of: (i) a definite concept and the close relationships between learning, adaptation and self-learning; and (ii) the underpinning mathematical apparatus are two of the most important achievements attributed to [1]. Speaking in their words, "…the problem of adaptation, learning and self-learning indicates that they are so closely related that it is amazing that this was not recognized earlier."

[15] There are numerous definitions of learning and adaptation. For the purpose of this manuscript and its simplicity it is assumed that the ability to learn is a precondition of the ability of being adaptable.

understand these expressions; and perhaps express themselves too.

The Co-operative system case studies addressed below help us envisage and understand how cognitive interactions between human and artificial beings may work (be achieved) within a particular living environment.

A. Human and Virtual Beings as Collaborative Partners in Computer Games

For humans, collaboration is a natural and beneficial medium with which to carry tasks, negotiate and achieve goals. In computer games, human players have worked together to achieve their objectives and many computer games today foster the need of being co-operative.

The motivation of the work presented in [24] was to explore and examine virtual beings engaging as equal partners with humans in co-operative computer games, resulting in richer, realistic emergent game play. There, it was postulated that human and virtual players are said to be Functionally Equal Partners (FEP) if and only if they both are: (i) provided the same ability when interacting; (ii) able to perform any role assigned to game players; and (iii) able to co-operate towards achieving the game common goals without any specific knowledge of the nature (human and virtual) of their fellow players.

To address this, the following research questions were identified:

- Can human and virtual beings, being heterogeneous agents, interact co-operatively in the context of computer games and what are the desirable attributes required for them to perform this co-operation as functionally equal partners?
- What computer game framework would be required to facilitate co-operation amongst functionally equal partners?
- How could such a collaborative computer game be designed and implemented in order to support human and virtual players engage co-operatively?

To answer these questions, a number of concepts were developed to create a framework for co-operative human and virtual beings. This was then expanded upon by the design, development and implementation of a co-operative computer game called TeamMATE[16] that supports human and virtual beings as functionally equal partners.

1) Co-operative Computer Game Implementation

The co-operative game engagement was defined, outlining the process by which partners produce outcomes collaboratively, and can be expressed formally as equal partners P engaged in the collaborative process c from which a set of outcomes O are met from the defined goals G:

$$O = c(P, G) \tag{2}$$

[16] Copyright © ICSL, Griffith University

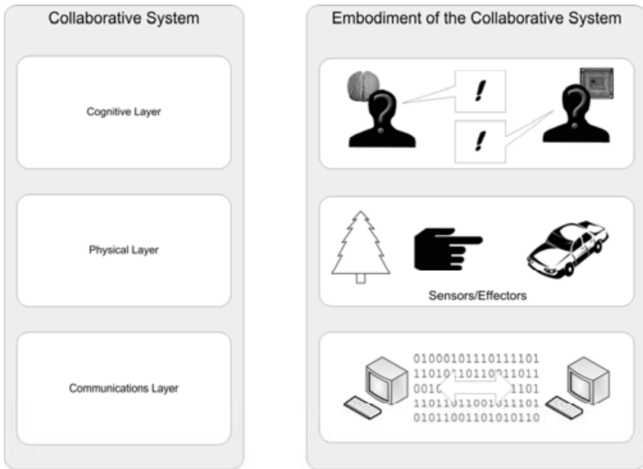

Figure 1. Cognitive, Physical and Communication Layers of the Collaborative Architecture

The process by which partners deliver outcomes based upon defined goals is achieved through the Co-operative Process: a process within which heterogeneous FEPs may engage to deliver outcomes.

TeamMATE was designed using a layered architecture which, consisting of the three major elements (Cognitive, Physical and Communication layers), offering flexibility and enabling consistency in achieving functional equality among human and virtual game players (Figure 1).

All elements of the implemented collaborative computer game were explored in detail including the computer game's three primary elements: The Game play environment, the Human Being Interface and the Virtual Being Interface. This included detailed process information, interfaces, software platforms and data. (Figure 2).

2) A Variety of Game Play Scenarios

Several game play scenarios were developed to demonstrate that the TeamMATE computer game can be effectively used to support FEPs in a variety of play scenarios such as entertainment; educational and business (corporate) decision-making type computer games.

Each case study implemented the concepts required to support FEPs in collaborative game play. In addition each case study explored a different attribute of collaboration, contributing to the understanding of the use and implication of the developed collaborative game concept.

These case studies demonstrated that the developed TeamMATE computer game enables human and virtual beings to interact co-operatively as functionally equal partners in the context of co-operative computer game settings. Finally, these case studies also show that TeamMATE, as an implementation of boardroom style collaborative computer games, may be used in entertainment, educational and business computer game applications.

Whatever the future holds for virtual beings, as FEPs they will no longer be props or plot devices in virtual worlds; but will be the players, teammates and co-workers of the future, working alongside their human counterparts (Figure 3).

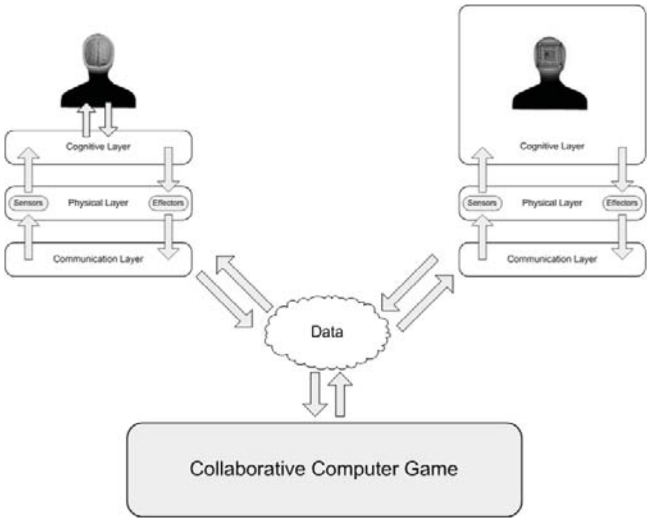

Figure 2. Humans and Virtual being collaboration faciliated by the Layered Collaborative Architecture within the Computer Game

Figure 3. A TeamMATE Collaborative Computer Game in Action

B. Co-operative Driverless Vehicles

Research into Intelligent Vehicles, and more specifically, Co-operative Driverless Vehicles has been led by the vision that in the not too distant future driverless vehicles will share the roads with vehicles driven by human beings [17]. That vision heralds a new era in the transport industry sector, offering the prospect of a sustainable urban mobility solution. Its wish is to free the city roads from accidents caused by human drivers. And indeed, the only way to enhance the road safety and achieve zero fatality on the roads is to replace human drivers by extremely reliable and fatigue-free intelligent machines.

The Intelligent Vehicle development concepts have been the subject of various research paradigms, the most notable being: (i) Driver Assistance, (ii) Autonomous (driverless) Vehicle and (ii) Co-operative Driverless Vehicles concepts.

The Driver Assistance technology may be used towards improving the driver's ability to control the vehicle, and if necessary, by taking corrective action. This may include the embodiment of versatile in-vehicle microcontrollers to: (i) warn the driver of hazards they have overlooked (e.g. collision warning, lane departure warning, pedestrian warning and driver fatigue warning); (ii) allow the driver to better control the vehicle should they find themselves in a dangerous situation; (iii) brake automatically if the driver fails to respond to warnings or if a situation occurs too quickly for the driver to respond; (iv) assist the driver to follow road lanes to prevent collisions with roadside objects and other vehicles; (v) assist bump-less driving in traffic congested situations; (vi) improve driver comfort by automating some of the more tedious parts of driving (for example, an adaptive cruise control maintains a vehicle's speed while ensuring a safe distance to the vehicle in front); (vii) assist the driver to park a vehicle; and so on.

The more advanced paradigm, an Autonomous (Driverless) Vehicle concept, enables a single, stand-alone (driverless) vehicle to drive independently along a road lane, typically segregated from the remaining road lanes.

Finally, the most advanced, the Co-operative Driverless Vehicles paradigm, enables many driverless vehicles to coexist on roads in co-operation with each other, road infrastructure and vehicles driven by human beings.

Being capable of operating on their own (without assistance from human beings) in either structured (a priory known) or unstructured (i.e. unknown) environments, co-operative driverless vehicles operate as fully autonomous systems. They sense all the objects from their surroundings, detect objects' motions, process the obtained information, predict likely changes, decide the best course of action, execute their decisions and then continue to watch the immediate surrounding environment to learn whether their actions have contributed to the improved performance of the controlled object, thereby learning what else would be required in order for the control system to fulfill its mission requirements with the best possible performance (Figure 4).

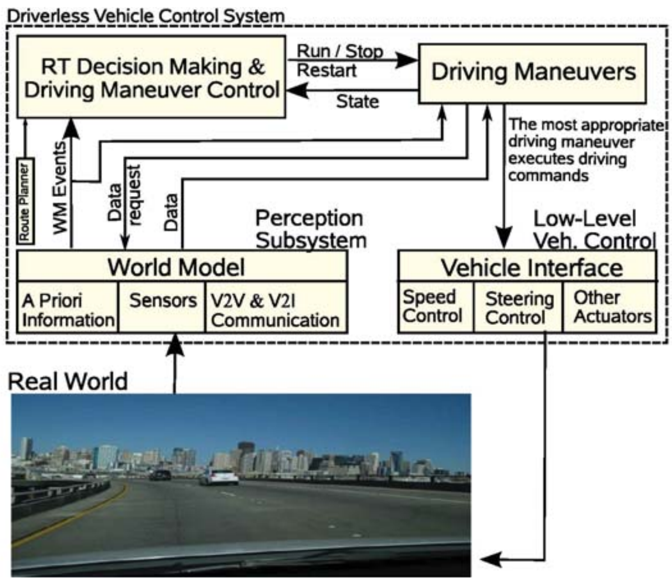

Figure 4. Driverless Vehicle Decision and Control System [25]

This is to say that co-operative driverless vehicles will soon become a part of the world about us, which consists of numerous interacting elements: itself becoming one of these interactive elements. Of course, they are expected to perform the dynamics of being co-operative at or near equilibrium and certainly not being far from equilibrium. Here, the role of Control Theory is to conceptually link all these elements, capture their correlations and make them form a closed-loop system with its own equilibrium dynamics[17].

It becomes now obvious that in order to be able to meet all these requirements; driverless vehicles need to be empowered with a cognitive ability toward understanding internal and external signals and become able to, in response to these signals, switch from one stable state to another (i.e. from one driving maneuver to another)[26][18].

These are the reasons why the reactive robotics paradigm, although being able to achieve remarkable results, has never been strong enough to facilitate the co-operative driverless vehicles concept and equip the vehicles with the necessary decision making power.

Over the course of numerous demonstrations, co-operative driverless vehicles successfully performed various driving tasks and maneuvers without any human interaction including a co-operative unsignaled intersection traversal (Figure 5) a co-operative overtaking maneuver (Figure 6) as well as a co-operative overtaking maneuver through interactions with vehicles driven by human beings (Figure 7) [27].

C. Co-operative Roundabout Driving by Driverless Vehicles

In recent times, roundabouts have become frequently a more accepted alternative in addressing the intersection problem, but at the same time are also becoming a conflictive point for many drivers [28]. Different studies have demonstrated that some drivers do not have experience using roundabouts. It is a cause of many traffic jams in the urban areas of large big cities [29], [30].

Figure 5. Co-operative un-signaled intersection traversal [17]

[17] Far from the non-equilibrium dynamics, typical for open-loop systems.

[18] This adaptive capability and the existence of multiple steady states are " distinguishing features of nonlinear dynamic systems" [26].

Figure 6. Co-operative overtaking maneuver [17]

Figure 7. Co-operative overtaking maneuver through co-operation with vehicles driven by human beings [27]

There are many types of roundabouts. Traditionally, the roundabout literature only considers the management problem, speed control, geometrical considerations and jam problems [30], [31], [32] and has not addressed roundabout driving performance by driverless vehicles. In this section, an algorithm that generates a map with parametric equations is briefly described. The algorithm postulates that each roundabout is defined by its radius and its center position in Cartesian coordinates. This reference information is generated in a route planner module (in the control stage, Figure 8) for the lateral control of driverless vehicle.

1) Control Scheme

The proposed control scheme is shown in Figure 8. It considers three main stages: Perception, Control and Actuation [33].

A brief explication of each stage is as follows:

a) Perception stage:

As Figure 8 shows, the perception stage has three main modules: the beacon information, the Human Machine Interface (HMI) and the sensor information.

The first module is in charge of transmitting information from the environment. In this case, only the radius and the center coordinates of the roundabout are needed to generate the map. Moreover, the beacon gives information about routes, actuating as a traffic signal, indicating an exit or other possible route.

The HMI module is just for activating an unexpected situation in the roundabout routine. For example, the driver changes lanes in the roundabout, and selects another exit once inside the roundabout. The HMI additionally is used, to change the speed reference, as well as abort the maneuver if necessary.

The last module provides information from the vehicle, using a GPS and a LIDAR. The GPS provides the information as a two-dimensional Cartesian coordinate system, and it is completely compatible with UTM coordinates used in real vehicle implementations with DGPS (the most recent DGPS have inertial systems for positions redundancy [33]. The LIDAR information is used to stop the vehicle when there is an obstacle in front of the vehicle.

b) Control stage:

The control stage consists of the following modules: the Route Planner, Emergency Situations and the Control Stage (Figure 8).

The Route Planner charges the predefined map, and it reads the information from the beacons (perception stage) to calculate the reference dynamic map. It is active when the vehicle is inside a roundabout, and it uses the parametric equations of the circle to extrapolate the real vehicle position to the reference. Figure 9 shows all the variables, points and roads used in the route planner. The tangent to the circle is just an approach to calculate the variables of the control system (*distance to the curve* and *the angular error)*. A projection of the line allows us to measure the variables with less error.

The second module is executed in parallel with the Route Planner. It can modify the action on the actuators if an emergency situation occurs. For example, a pedestrian crossing the street unexpectedly results in the vehicle being stopped.

The Control Stage calculates the actions over the vehicle actuators considering the reference given by the Route Planner. Different control strategies can be used for this block. Two variables feed two independent proportional controllers (*distance to the curve* and *the angular error*) [34].

c) Action stage

This stage is in charge of moving the vehicle's actuators: steering and pedals (Figure 8). It receives the target from the beacon information and the HMI. The simulator used in this work allows an action interval between [-0.5 ; 0.5] for the steering wheel and [-1 ; 1] for the brake and throttle [33], [34].

2) Simulations on roundabouts

Two experiments have been carried out to show the behavior of the driverless vehicle on a standard roundabout of an eleven meter radius.

Figure 10 shows a continuous turning in the roundabout, doing lane changes inside the roundabout. In this case, we are checking the dynamic behavior of the driverless vehicle on the roundabout.

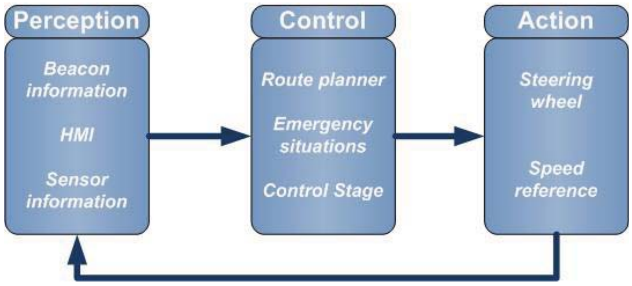

Figure 8. Control Scheme of the Cyber car.

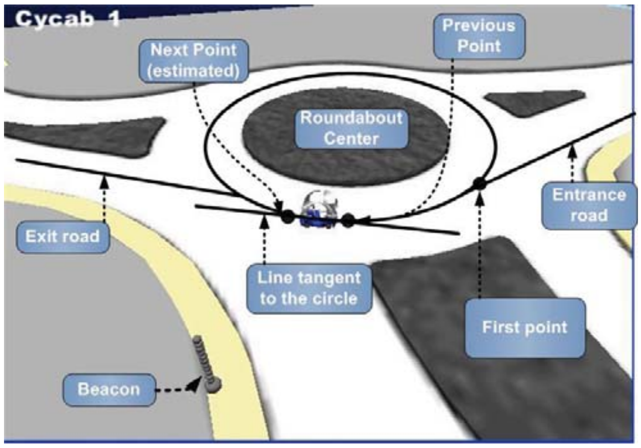

Figure 9. Variables used for the route planer

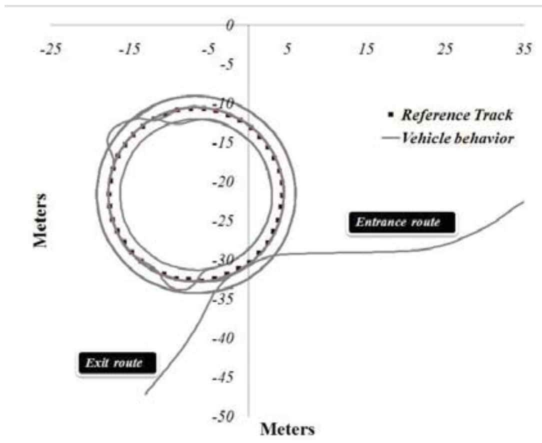

Figure 10. Cybercar's behavior on the roundabout, lane change maneuver taking the first exit.

The distance of the vehicle to roundabout center is shown in Figure 11.

Finally, the second experiment considers exiting using the second exit out of the roundabout as shown in Figure 12.

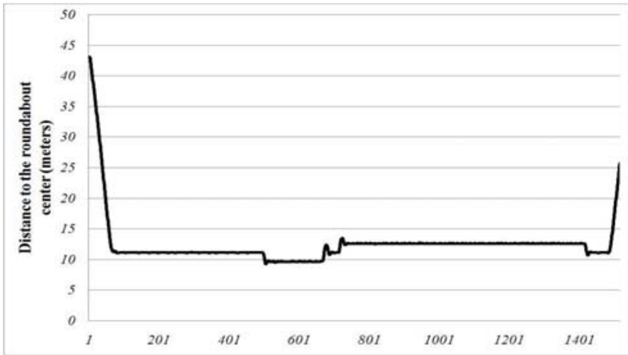

Figure 11. Distance of the vehicle to the roundabout center

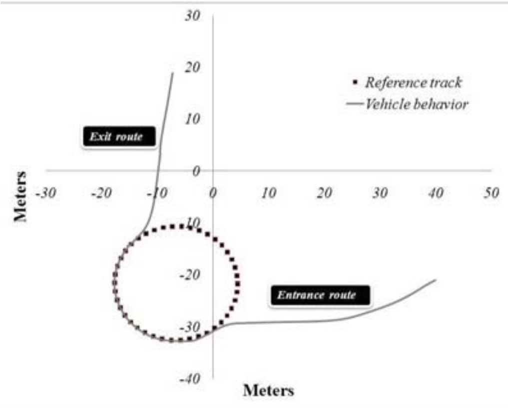

Figure 12. Driverless vehicle's behavior taking the second exit on the roundabout

3) Some Observations

These simulations show a good behavior of the control scheme proposed in this work. Figure 10 and Figure 11 show the automatic reference track (inside the roundabout) generation using circle parametric equations. Figure 9 shows the behavior of the vehicle when lane change maneuvers in the roundabout are performed. The trajectories tracking on each different radius are quite good. Figure 11 shows some little overshoots that the driverless vehicle experiences when it is doing a lane change inside the roundabout. This behavior is negligible since it is to demonstrate the robustness of our control scheme; and not for real situations.

Figure 12 shows a real situation on roundabouts. This experiment shows the driverless vehicle entering the roundabout, moving across the center line, and then taking the exit (using the HMI module).

All the information regarding free exits, on line inside the roundabout has been provided through the vehicle-infrastructure communication with the beacons.

VI. CONCLUDING REMARKS

Contemporary research into co-operative systems is at its prominence. A research challenge is in enabling human beings and artificial beings to interact and co-operate in real time and in a dynamic and reliable way; and, in enabling artificial beings to become our partners in the workplace and home, to respond to our requests and, not just recognize our routine, but tune themselves to our specific needs. The acceptance of co-operative systems is subject to their ability to surpass a failure of any of its components and continue to successfully operate under adverse conditions. Since the future is in collaborative relationships between human and artificial beings, having the latter capable of adapting themselves to the ever changing needs of human beings, the next research challenge is in understanding how cognitive interactions between human and artificial beings may work (be achieved) within a particular living environment.

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