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A HARMS-based heterogeneous human-robot team for gathering and collecting

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Abstract. Agriculture production is a critical human intensive task, which takes place in all regions of the world. The process to grow and harvest crops is labor intensive in many countries due to the lack of automation and advanced technology. Much of the difficult, dangerous and dirty labor of crop production can be automated with intelligent and robotic platforms. We propose an intelligent, agent-oriented robotic team, which can enable the process of harvesting, gathering and collecting crops and fruits, of many types, from agricultural fields. This paper describes a novel robotic organization enabling humans, robots and agents to work together for automation of gathering and collection functions. The focus of the research is a model, called *HARMS*, which can enable *Humans*, software *Agents*, *Robots*, *Machines* and *Sensors* to work together indistinguishably. With this model, any capability-based human-like organization can be conceived and modeled, such as in manufacturing or agriculture. In this research, we model, design and implement a technology application of knowledge-based robot-to-robot and human-to-robot collaboration for an agricultural gathering and collection function. The gathering and collection functions were chosen as they are some of the most labor intensive and least automated processes in the process acquisition of agricultural products. The use of robotic organizations can reduce human labor and increase efficiency allowing people to focus on higher level tasks and minimizing the backbreaking tasks of agricultural production in the future. In this work, the *HARMS* model was applied to three different robotic instances and an integrated test was completed with satisfactory results that show the basic promise of this research.

Keywords: multi-robot system; multiagent system; HARMS

1. Introduction

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Basic fruits are an important crop utilized and depended on as a staple food in the diet of many people. This dependence spans many parts of the world and is of particular importance in many parts of Asia. The process to harvest fruits and some vegetables is not currently as automated as many other dependent staple crops across the world such as wheat, corn or sorghum. These crops are produced in large fields with efficient techniques, large machinery and mass production. Unlike these crops, the production of fruits and other gathered crops remains a very human labor-intensive practice. Given the statement of belief by the IEEE Robotics and Automation Society (2014), the automation of agriculture can be enhanced with robotic, and therefore agent-oriented systems.

Agriculture is humankinds oldest and still its most important economic activity, providing the food, feed, fiber, and fuel necessary for our survival. With the global population expected to reach 9 billion by 2050, agricultural production must double if it is to meet the increasing demands for food and bio-energy. Given limited land, water and labor resources, it is estimated that the efficiency of agricultural productivity must increase by 25% to meet that goal, while limiting the growing pressure that agriculture puts on the environment. Robotics and automation can play a significant role in society meeting 2050 agricultural production needs. For six decades robots have played a fundamental role in increasing the efficiency and reducing the cost of industrial production and products.

Much of the difficult labor of fruit production can be automated with intelligent and robotic platforms. We propose an intelligent agent architecture, which can use sensors, robots and agricultural machinery to automate the process to gather and collect crops, so that a robot can minimize or eliminate human labor in the fields. The difficulty in picking and collecting basic fruit crops is abstract to a human, given our dexterity, physical traits and ease to pick fruits from trees or bushes. But, we take for granted the capabilities to pick fruits such as berries, shown in Fig. 1 or apples, shown in Fig. 2. While these two fruits are commonly consumed and easy for a human to pick, collect and gather, it is very complex to develop a machine to perform the range of tasks with equal capability. Previous studies in this area have endeavored to facilitate picking of cherries (Tanigakia *et al*. 2008) and other general fruits (Hayashia *et al*. 2010), as examples of the opportunities as well as difficulties in this task.

This problem and need for technology, such as sensors, machines, robots and *HARMS* architectures are as much of an economic issue as it is a labor, safety or agricultural issue. A short supply of labor can seriously hinder crop production and create massive ripple effects in the food supply.

As the human drive to communicate directly to robots (Rani *et al*. 2008) and other non-human actors increases and becomes more common place in some configuration of artificial communication, it is equally important to speak with other classes of cyber-physical systems, as shown by Erickson 2004. In the near future, ubiquity in this technological area will provide near-human communication with a range of devices in which humans interact on a common and daily basis. The foundation is set by Kim *et al*. (2004) by defining the need for ubiquity in robotics. A ubiquitous future leans to the notion that we can give commands or request services (Yachir *et al*. 2009) to any range of cyber-physical systems capable of accomplishing a specific task without regard to the physiological or cognitive definition of the system. In terms of multi-agent or artificial, organizations, there is typically a goal to accomplish. If an actor in the organization announces a task to all other actors, the first actor only cares that the task is accomplished, but not necessarily concerned with who carries out execution, within reason. The actor who executes the task must be capable of executing the task to accomplish the goal. There may be many actors, in

Fig. 1 Berries-Purdue farm

Fig. 2 Apples-Purdue farm

the organization, with this capability and these actors may all be different, in terms of class, embodiment, mobility and physiology. For example, a person can ask for someone to get a morning newspaper from the lawn. A human, dog or robot can accomplish this task, as all have capability. If the requester can give a general command that each can understand then any can execute this task to satisfy the goal of getting the paper. Thus, given that all can understand the command, it is a request ubiquitous to all actors but indistinguishable who must execute the task, given that all are equally or necessarily capable. One of the most recent research work in the field of task allocation in organizational multi-agent systems is reported in (Esmaeili *et al*. 2017). In this work, the authors have proposed a dynamic method in which the agents try to group together to form organizational structures to execute the incoming tasks. The strength point of the suggested method is that it does not utilize any external forces to manage the formation of the groups and performing the tasks.

This research is an extension of an initial work (Lewis *et al*. 2012) and a specific publication extension (Kim *et al*. 2015). This remainder of this paper is organized with section 2 showing the *HARMS* model to enable work in large cyber-physical organizations. Section 3 shows the realization of a robotic system to implement and allow testing of the model. Section 4 provides some initial results of the system and section 5 and 6, respectively, provide conclusions and planned future extensions to this research work.

2. HARMS Layered model

As robots become more pervasive and ubiquitous in agriculture, they become increasingly involved in the lives of humans. Farmers and those involved in production agriculture expect robots will take on tasks to ease their lives, by working with humans just as other humans do, in normal organizations and teams. This labor specialization, by ubiquitous robots, allows humans more comfort, time or focus to concentrate on higher level desires, tasks or goals. To further this unification of cooperative relationships, the defined line between humans and other robots must become somewhat indistinguishable.

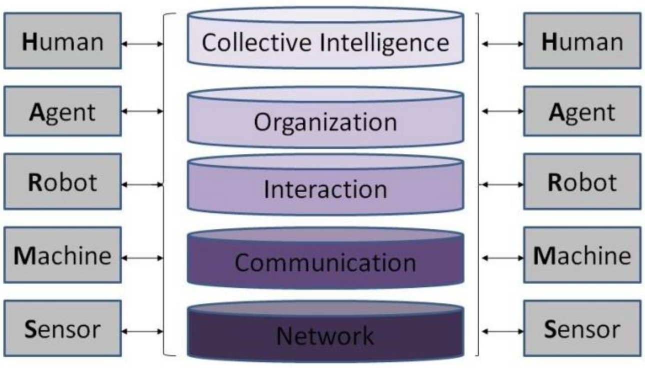

Fig. 3 HARMS layered model concept

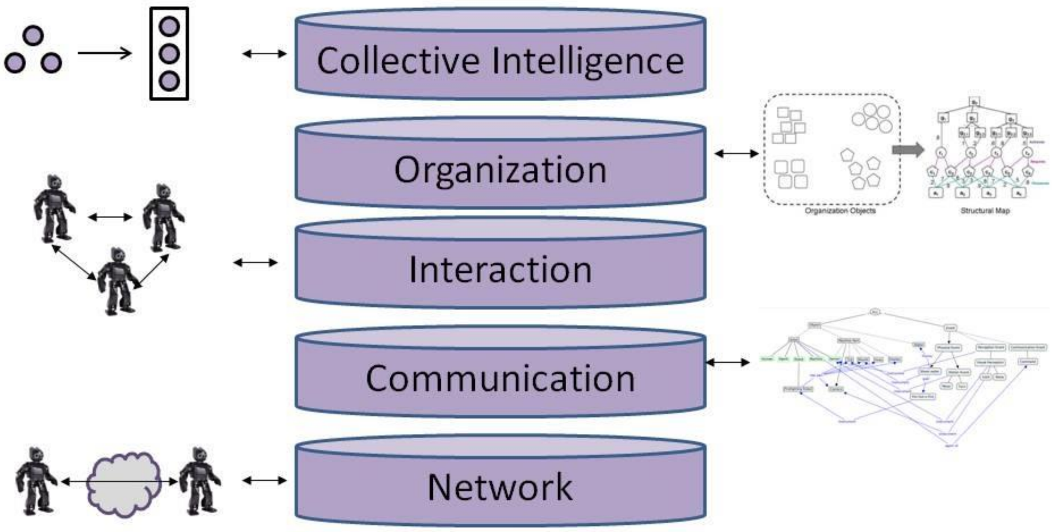

Fig. 4 HARMS functionality

This ever-increasing degree of indistinguishability provides that we care less about who or what executes a task or solves a goal, as long as that acting entity is capable, functional and available. In this section, we propose an on-going developing model and a simple example implementation which minimizes the strict line between humans, software agents, robots, machines and sensors (*HARMS*) and reduces the distinguishability between these actors, which can be applied to many task domains, specifically gathering and collection, in this work.

The development of an organization, which supports indistinguishability within its members requires a model definition enabling these actors to connect, communicate and interact. Secondly, the model must support actors of many different cyber-physical definitions. In this research, we have defined a model to connect *humans*, software *agents*, *robots*, *machines* and *sensors*, called the *HARMS Model*, where each layer of the model, previously introduced (Matson and Min 2011, Matson *et al*. 2011) integrates with the layers above and below it, as shown in Fig. 3. The abstract goal of this effort is the integration of humans and non-human actors, in this case, humanoid robots and unmanned ground robots. The control of a human and non-human system has explored in terms of control (Lim *et al*. 2009, Meteb *et al*. 2016), more specifically formation control (Hsu and Liu 2007) and collaboration (Bauer *et al*. 2008) of human and non-human actors. This category of research is the basis for investigation into a *HARMS* model and architecture.

The end goals are artificial organizations, which can exhibit not only the organizational capabilities of humans but go beyond to the state of evolution where cultural and social normative behavior emerges in the non-human organizations. The model in Fig. 3 shows the 5 layers with collective behaviors, as the highest layer. Achievement to this level extends the ability of labor-strapped agriculture sectors to perform at a more human replacement level. The application of this type of artificial organization function has potentially far reaching economic impacts and can lessen the stress of labor fluctuations caused by social, economic, government or legal forces.

Each of the layers in Fig. 4 is connected to the layers immediately below or above it in the model. Layers higher in the model depend on the lower layer's function and service. For example, the ability of an agent to communicate depends on its ability to network with another agent. The layers are presented from the lowest layer to the highest. The level does not represent the level of abstraction in the model.

2.1 Network

The *Network* layer represents the basic communication between the system actors. Each system actor must have basic network capabilities to connect to other actors. In this case, actors will connect via a wired or wireless network to any other system actor. In this model, networking represents the physical connection between actors. The actors have the capability to communicate via sending TCP/UDP messages using *unicast*, *multicast* or *broadcast*, depending on the message type and set of actors the communication is directed towards. For example, a robot can connect to several sensors and send them a TCP multicast message.

2.2 Communication

The *Communication* layer enables the basic *common exchange capability* between any systems actors. Communication is defined by elements such as meaning, syntax, protocols and semantics (Hidayat *et al*. 2008). This layer is modeled in a generic sense to allow any actor to communicate in many ways, including natural language, gestures, simple text and many other possibilities. This layer enables any *n* actors to communicate via a standardized, understandable interface and is dependent on the ability of actors to network, in the lower level. An example is the same robot, sending a text message via multicast to several sensors, in using natural language such as English.

2.3 Interaction

The *Interaction* layer represents a set of common, well understood algorithms and techniques which provide a layer for group rational decision making by a set of actors, such as voting, auctions and also some new models, such as hierarchical decisions. Common economically-driven and market-based algorithms provide a basis for this layer typical to the description in Weiss (1999). In this system, there is a collective, cooperative interest in which there exists negotiation and bargaining between agents for decision-making. These layers depend on the actors' ability to effectively communicate from the layer 2 functionality. An example will be a robot, using the network and communication layers to effectively send a message to the sensors for getting a temperature reading, then voting on which sensor is the most precise and capable.

2.4 Organization

The *Organization* layer uses multiagent systems organization models such as OMACS[3], enabled by networking, communication and interaction services provided by the *HARMS Model's* three lowest levels. The organization layer provides for the needed group rational decision-making required to organize based on capability, around a set of common organizational goals. Each of the actor's possess specific capabilities required to play a role in an organization. Each role can work to solve a set of 1 to *N* goals. The overall set of organization goals can be accomplished by the aggregate set of roles, played by the diverse actors, available to be active in the organization.

2.5 Collective intelligence

The *Collective Intelligence* behavior in a collection of agents, robots and humans can lean in a number of different directions. In this case, we focus on collective organizations with emergent and planned behavior. Examples are the societal or organizational norms, which exist in a collective (Grizard *et al*. 2007, Savarimuthu *et al*. 2008) or models of social agreement in agent societies by Lorini and Verdicchio (2010). The collective intelligence will not only allow emergent behaviors, but also the connection of multiple organizations into higher-level collectives such as societies or organizations, and potentially a definition of consciousness (Raskin *et al*. 2012).

2.6 Indistinguishability

The concept of indistinguishability is not a layer in the *HARMS Model* but is a concept the HARMS Model will enable. Indistinguishability enables a system to choose between *n* different options of minimally capable actors relative to some task or goal. If there are a number of heterogeneous actors, each with the capability, the selection is not dependent on a specific embodiment, physiology or cognitive design. Capability to solve the systems goals, potentially within a temporal constraint, is the only distinguishing factor between indistinguishable actors, in a system. For example, asking a cheap temperature sensor or a human what is the temperature will result in two valid answers. But, the cheap temperature sensor is more capable of providing an accurate and more precise answer than the human. So, if a HARMS message is sent to both a cheap temperature sensor and a highly capable human, the temperature sensor will be selected, but indistinguishably.

3. HARMS communication

For this research, the bulk of work is in the first two layers of the HARMS model implementation. A basic example of this is shown in Fig. 5. Each actor will possess access to a HARMS five-layer stack in their computational infrastructure. For agents, robots, machines and sensors, the interface is fairly self-explanatory. For humans, the human has two basic options; 1. Interact with a device that allows an obvious interface such as a computer, cell phone or TCP-enabled device, or 2. The human using natural language or some non-TCP-enabled form of natural communcation. In Fig. 5, the example shows a human, DARwIn robot (Robotis 2015) and a temperature sensor. In a simple example where a human asked the DARwIn to discover the temperature in the room, the DARwIn does not have a viable temperature sensor, so it sends a message to an available actor, which is capable to provide this information and solve the overall system goal. To accomplish this, the human will connect to DARwIn then communicate a query. Then, DARwIn will connect to the temperature sensor to propagate the query. The temperature sensor will answer to the DARwIn and in turn, will propagate the answer to the human.

The *HARMS* model (Matson *et al*. 2011) assumes communication in a semi-formalized language format between all actors. To appear indistinguishable, the actors will communicate in English, or another natural language subset, limited lexically for a restricted domain, but fully conforming to the rules of the specific morphology, syntax and semantics. The actors will exchange messages in terms of questions, directives and information messages. Given the actors can send messages via unicast *u*, multicast *m* or broadcast *b*, they can send from $actor_a$ to any

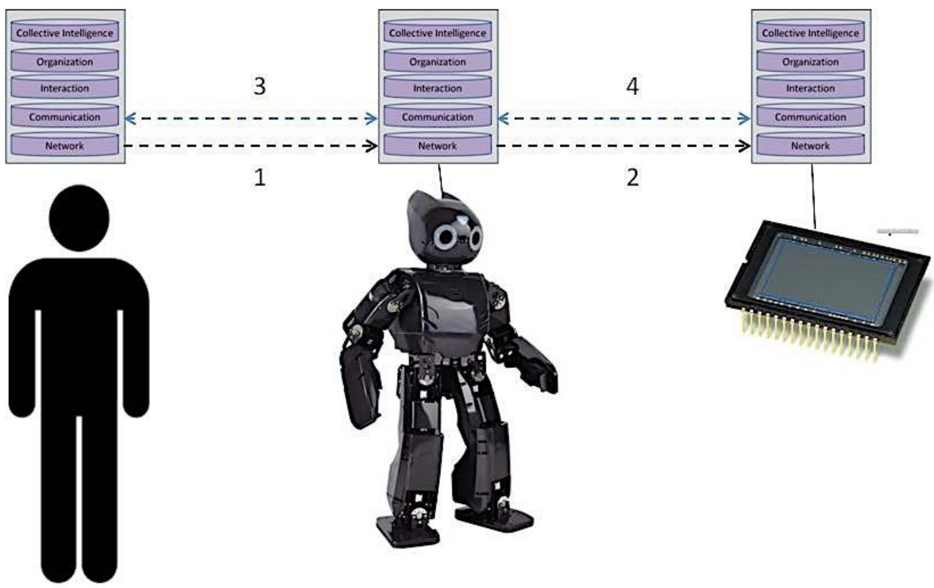

Fig. 5 HARMS Communication

$actor_b \ldots actor_\infty$. The set of actors *Act* is defined by $Act = \{H, Ag, Ro, M, S\}$ where *H* is a set of humans, *Ag* is a set of agents, *Ro* is a set of robots, *M* is a set of machines and *S* is a set of sensors.

There are 3 basic communication functions in the system; *questions*, *messages* and *directives*. An example of a common command is:

drive forward then stop and retrieve apple

Realistically, there are three commands here, so it will be broken down into a set of sequential commands. The next three subsections describe the basic structure of *questions*, *messages* and *directives* and then a subsection on implementing a directive.

3.1 Questions

Questions send a message *msg* to a group of $\{n\ actor_s \mid actor_s \in Act, n \in \aleph\}$ and return a *msg* back to $actor_x$, the inquiring agent. Content of the functions is dependent on the domain structure and problem.

$$msgx \leftarrow questionactorx\,(actory, msgy, u) \tag{1}$$

Each *question* function has unique parameters, based on its problem and audience. Eq. (1) represents $actor_x$ asking a message *msg* of only $actor_y$ as the third parameter *u* represents a *cast* function, which can be *unicast*, *multicast* or *broadcast*.

$$\{msgx,y \mid x,y \in Act\} \leftarrow questionactorx(\{actory\_1 \ldots actory\_n\}, msgy, m) \tag{2}$$

Eq. (2) represents $actor_x$ asking a question message *msg* of to all actors in the set $\{actor_{y\_1} \ldots actor_{y\_n}\}$ as the third parameter *m* represents a *multicast* function, which targets an inquiry to a select group of actors. The function returns a set of messages from each actor.

$$\{msgx,y \mid x, y \in Act\} \leftarrow questionactorx\,(msgy, b) \tag{3}$$

Eq. (3) represents $actor_x$ asking a question message *msg* of to all actors in the organization as the third parameter *b* represents a *multicast* function, which targets a question to a select group of actors. The function returns a message from each actor.

3.2 Messages

The *Message* function sends a message to a group of *n actors*, without any return. Eq. (4) represents $actor_x$ sending a message to a single $actor_y$.

$$Messageactorx\,(actory\ , msgy\ , u) \tag{4}$$

Eq. (5) represents $actor_x$ sending a message to all actors in the set $\{actory\_1 \ldots actory\_n\}$.

$$Messageactorx(\{actory\_1 \ldots actory\_n\}, msgy, m) \tag{5}$$

Eq. (6) represents $actor_x$ sending a message to all actors.

$$Messageactorx\,(msgy\ , b) \tag{6}$$

3.3 Directives

The *Directive* function sends a command to a group of *n actors*, without any return. Eq. (7) represents $actor_x$ sending a message to a single $actor_y$. The basic assumption is in a cooperative system, all agents will obey and honor the command.

$$Directive_{actorx}\ (actor_y\ ,\ msg_y\ ,\ u) \tag{7}$$

Eq. (8) represents $actor_x$ sending a directive command to all actors in the set $\{actor_{y\_1} \ldots actor_{y\_n}\}$.

$$Directive_{actorx}(\{actor_{y\_1} \ldots actor_{y\_n}\}, msg_y, m) \tag{8}$$

Eq. (9) represents $actor_x$ sending a directive command to all actors.

$$Directive_{actorx}\ (msg_y, b) \tag{9}$$

3.4 Implementing a directive

The example of a common command directive is *drive forward then stop and retrieve apple*. This directive is compound as there are three commands here to drive, stop and retrieve. Also, two directives have a sub-directive, forward and apple, respectively. For example, we can send this directive to a single actor, a group of actors or all actors, in a system.

For a single directive, the robot in question will be named George from the source actor Bob. The message sequence will be:

DirectiveactorBob(*actorGeorge*, *msgdriveforward*, *u*)

then

DirectiveactorBob (*actorGeorge*, *msgstop*, *u*)

and finally

DirectiveactorBob (*actorGeorge*, *msgretrieveapple* , *u*)

The assumption is the configuration and capability on-board any *HARMS* actor allows correct execution of the directive.

4. Realization

The ultimate goal is to pick up all of the fruits (balls), which simulate agricultural products and move them to a collection point, typically near a human. In a real scenario, the fruit would be loaded onto a transport and moved to a cleaning and preparation facility for final packing and storage, prior to being shipped to a retail outlet. This realization only looks at the field picking operation with a set of robots acting as pickers and movers to the collection point. The focus on picking and collection is due to those tasks being the most labor-intensive.

This experiment is not appropriate for all picking and collection scenarios in agriculture, such as harvesting grain crops, as that is already highly mechanized. This work focuses on high value crops such as field-based or orchard-based fruit picking. Specific examples area an apple orchard, ground fruit and low plant fruit fields. This would be such fruits as picking apples off low trees, picking strawberries from low plants or picking blueberries from small bushes. While the robots in this experiment are too small to necessarily adapt to all three scenarios, the basic concept for the work can be realized.

To realize this *HARMS* oriented project, with heterogeneous robots working together, we constructed a field with different-colored balls to represent fruits on the ground. The robots gathered the balls as substitutes for the fruits, as the complexity of just picking a fruit without crushing it is beyond the scope of this work. The focus of this work is the logistics of picking and collection. The human is the initiating actor in this experiment.

In this section the human and non-human actors are defined, followed by a description of the system goals. Finally, the process and control of the system are described.

4.1 Actors

In this experiment, three heterogeneous robots and a human are utilized. The *human* $actor_{Human}$ is the originator of commands. The *DARwIn* humanoid robot $actor_{DARwIn}$ is used as the fruit picker and collector, as it has both capabilities. An *iRobot Create* (iRobot 2014) with a basket on the top is used as a collector $actor_{Collector}$. Another *iRobot Create* is configured a specialized bulldozer $actor_{Bulldozer}$ robot, to gather fruit already on the ground by pushing it to the collection point.

Each actor will utilize the lower two layers of *HARMS*, *networking* and *communication*, as shown in Fig. 5. For all communication, a combination of Zigbee connection and IEEE 802.11 wifi protocols were used to connect the robots.

4.2 Goals

Our first goal is to enable $actor_{DARwIn}$ find the fruit and pick them up as in Fig. 6. And drop the ball into a basket on top of $actor_{Collector}$, shown in Fig. 8 which is the transporter, or the basket, which is located at designated collection point. Where the $actor_{DARwIn}$ will drop fruit depends on the proximity to each point.

The picking capability of the $actor_{DARwIn}$ with a prehensile gripping hand, as shown in Fig. 6, could only collect 1 fruit per pick, so the hands were rebuilt with custom scoop boxes on each arm as shown in Fig. 7. This forms a box that allows scooping the fruit and ease of picking without damaging the fruit.

The second goal is autonomous control the $actor_{Collector}$ in order to carry balls from $actor_{DARwIn}$ to a human-based collection point. The final goal is to enable the $actor_{Bulldozer}$ to gather and assemble balls at the designated spot and go back to the original starting location. This is similar to gathering fruit on the ground as shown in Fig. 2. As the robots go through these steps to goal completion they will network together and communicate using a *HARMS* model instance in each robot to enable the cooperative work. Fig. 9 shows the operational flow chart of activities for the fruit picking system as it goes through completion of the system goals.

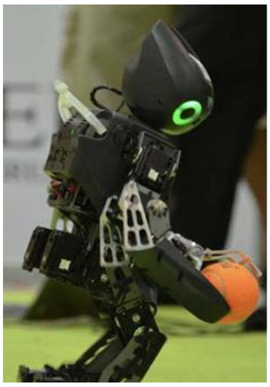

Fig. 6 Ball picking humanoid $actor_{DARwIn}$

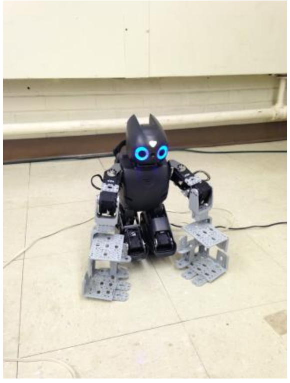

Fig. 7 Ball picking $actor_{DARwIn}$

Fig. 8 Collector $actor_{Collector}$

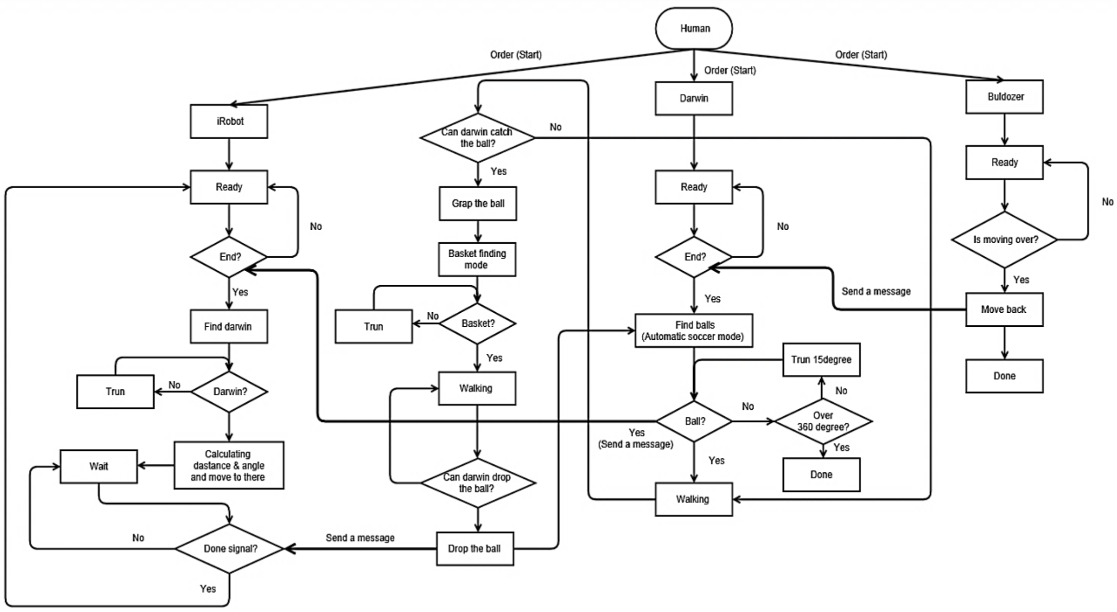

Fig. 9 HARMS Flow chart for the ball picking system

Fig. 10 $actor_{DARwIn}$ vision

4.3 Process and control

As bootstrapping a completely autonomous system has some intrinsic complexities, the $actor_{Human}$ will initiate this process. To start the system, $actor_{Human}$ gives 2 commands to the robot team to collect all fruits, $Directive_{actorHuman}(actor_*, msg_{collect}, m)$ and bring the fruits to the collection point, $Directive_{actorHuman}(actor_*, msg_{destination}, m)$. These commands are structured in the format as previously described. The $actor_{Bulldozer}$ begins to assemble all of balls at the destination coordinates. When the task is completed, the $actor_{Bulldozer}$ sends a message, "task complete" to all others. Then, $actor_{Bulldozer}$ returns to the point of origin. A diagram of the interaction is shown in Fig. 12.

Then, the $actor_{DARwIn}$ initiates motion and uses color-based vision to find the fruit as shown as Fig. 10. Once $actor_{DARwIn}$ finds a ball, he sends a message to the $actor_{Collector}$ to "follow me" to let the $actor_{Collector}$ receive the fruit from $actor_{DARwIn}$. When $actor_{DARwIn}$ retrieves the fruit, he then locates the $actor_{Collector}$ to drop it into the moving basket of $actor_{Collector}$. If there is no basket in $actor_{DARwIn}$ range of view, $actor_{DARwIn}$ will rotate until it finds the $actor_{Collector}$.

Then, $actor_{DARwIn}$ conveys the ball to a ball basket installed on the $actor_{Collector}$. To do this step, the $actor_{DARwIn}$ sends a message to $actor_{Collector}$ to call and position next to $actor_{DARwIn}$. $actor_{Collector}$ will receive that message "follow me" from $actor_{DARwIn}$ and then he will start to move to find the $actor_{DARwIn}$ and calculate the distance and angle between $actor_{DARwIn}$ and iRobot to go near $actor_{DARwIn}$ as shown in Fig. 11. When the $actor_{DARwIn}$ approaches to place the ball, the moving basket of $actor_{Collector}$ will wait the ball is fully dropped off into his basket. When the set number of balls have been collected, the $actor_{Collector}$ will move to the initial collection point, co-located with the $actor_{Human}$.

By using this approach, the fruits, randomly distributed on the floor, can be collected quickly and efficiently.

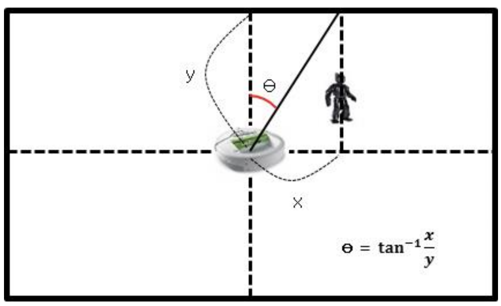

Fig. 11 Co-location and following

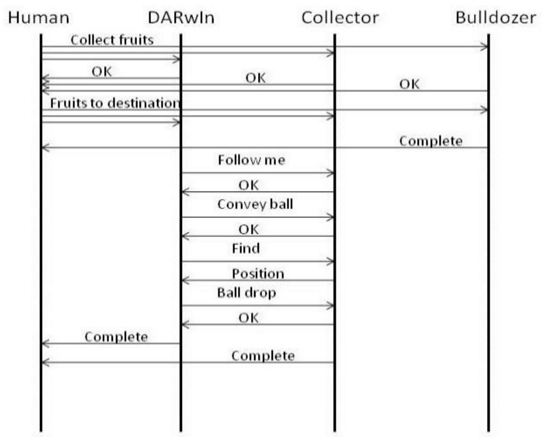

Fig. 12 Interaction of all actors in the system

5. Experiments and evaluation

Testing was conducted in a controlled lab environment for this initial experiment. The test range was an indoor smooth floor with varying size. There were 4 sets of experiments starting with the same initial state but differing in the constitution of the robot team. Every experiment has same initial state as shown Fig. 13. Each experiment has red balls in a row and a yellow basket in the corner. The goal of the experiments is to put all balls to the yellow basket.

In the test environment, there are a total 4 agents; $actor_{Human}$, $actor_{DARwIn}$, $actor_{Collector}$ and $actor_{Bulldozer}$. Each robot has its positives and negative attributes and capabilities, as shown in Table 1. These varying capabilities and the ability to communicate to solve a goal through the HARMS implementation, drives the results, and affects to HARMS multi-actor system. It enables the

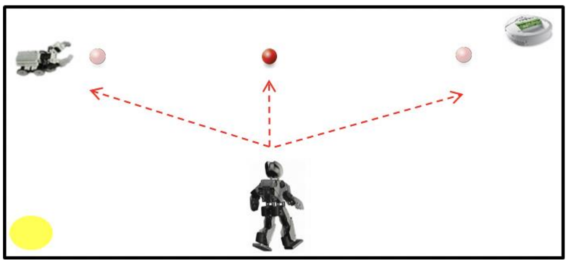

Fig. 13 Initial test environment

Table 1 Positives and negative capabilities of each actor

Robot	Positives	Negatives
$actor_{DARwIn}$	Can pick up the ball Find the basket Drop the ball into the basket	Slow movement
$actor_{Bulldozer}$	Control multiple balls	Cannot pick up a ball
$actor_{Collector}$	Fast movement	Cannot pick up a ball

Table 2 Total elapsed time of ball picking as a result of differential actor combinations

	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Robot	DARwIn	DARwIn, Bulldozer	DARwIn, Collector	DARwIn, Bulldozer, Collector
Trial 1	124 sec	103 sec	114 sec	92 sec
Trial 2	124 sec	112 sec	110 sec	92 sec
Trial 3	113 sec	110 sec	101 sec	92 sec
Trial 4	119 sec	104 sec	101 sec	92 sec
Trial 5	119 sec	102 sec	98 sec	92 sec
Average	119.8 sec	106.2 sec	104.8 sec	92 sec

Table 3 Task and participation of each actor

Actors	Interaction	Experiment* 1 2 3 4
Human, DARwIn	DARwIn moves only when human sends a signal to start	OOOO
DARwIn, Bulldozer	Bulldozer moves 2 secs after DARwIn has started to move	XOXO
DARwIn, Collector	Collector moves only when DARwIn has noticed a ball	XXOO
Human, Collector	Human controls iRobot	XXOO

*Experiment: O represents actors participated in the corresponding experiments, while X represents actors did not participate in the experiments

HARMS system efficiency by providing suitable positions for each robot. We attached the yellowbasket to iRobot in order to enable a moving basket because of consistent movement. In each experiment, Darwin picks a set of balls, the $actor_{Bulldozer}$ collects the balls to the end point, the $actor_{Human}$ controls the iRobot, and the $actor_{Collector}$ waits for $actor_{DARwIn}$ until it drops a ball. The experiment initiates when the $actor_{DARwIn}$ receives the initial input signal. Experiments are shown in Table 2.

5.1 Results

There are 4 different experiments performed; only $actor_{DARwIn}$, $actor_{DARwIn}$ with $actor_{Bulldozer}$, $actor_{DARwIn}$ with $actor_{Collector}$ and $actor_{DARwIn}$ with $actor_{Bulldozer}$ and $actor_{Collector}$. So, overall system shows that the closer organization robots, the faster the work can be done, relieving the human of labor.

Experiment 1 took 119.8 seconds in average to carry 3 balls, and it showed that with only the $actor_{DARwIn}$, it is hard to achieve great performance because of slow walking and inaccurate vision processing. In experiment 2, we added the $actor_{Bulldozer}$ to complement the $actor_{DARwIn}$. According to Table 2., it communicates with the $actor_{DARwIn}$ and it collects the three balls to one place, so it reduces the total elapsed time to shorten the $actor_{DARwIn}$ walking distance. Therefore, experiment 2 took 106.2 second in average which is a better result than experiment 1.

In experiment 3, we used $actor_{DARwIn}$ and $actor_{Collector}$. The $actor_{Collector}$ initiates movement after $actor_{DARwIn}$ has noticed a ball. It follows the $actor_{DARwIn}$ with a ball with the basket, so $actor_{DARwIn}$ can shorten the travel to the basket and overcome its weakened capability. The $actor_{Collector}$

following function saves $actor_{DARwIn}$ walking travel time, so experiment 3 also has better result (104.8 sec) than experiment 1.

In experiment 4, we used all robotic agent actors to maximize the efficiency of the *HARMS* team, even though it is the most complex system, requiring the most communication. The $actor_{Human}$ initiates by sending a signal to $actor_{DARwIn}$, then $actor_{DARwIn}$ starts to move. The $actor_{Bulldozer}$ starts to collect all balls after 2 seconds. When $actor_{DARwIn}$ sees the ball, the $actor_{Collector}$ starts to follow the $actor_{DARwIn}$. In this scenario, the *HARMS* system minimizes $actor_{DARwIn}$ slow walking time, so it maximizes the efficiency. The result of experiment 4, taking the shortest time, shows the best use and capability of this system (Table 3). Each robot has somewhat maximized their advantages and minimized their shortcomings, and it finally maximizes the relative efficiency. This shows the ability to capture capability to minimize time, maximize efficiently and utilize specialization of labor.

6. Conclusions

Production agriculture is a critical human survival and growth effort, but also an intensive human task which takes place in all parts of the world. The investment, time and process to grow and harvest fruit cops is expensive partly due to the nature of intense human labor involvement. Much of the human involvement is due to the lack of automation and advanced technology. These difficult, dangerous and dirty crop production tasks can and should be automated with intelligent and robotic platforms, for labor, economic, security and sustainability reasons. We propose an intelligent, agent-oriented robotic team, which can enable the process of harvesting, gathering and collecting crops and fruits, of many types, from agricultural fields.
The goal of this research is to create a *HARMS* prototype to demonstrate a multi-actor system integrated to act in an agricultural task domain and save labor, in that function, to show that capability-based robots can be employed in intensive human labor tasks to reduce involvement in dirty, dangerous and dull activities. Thereby, saving economic labor costs and spurring financial savings through capability-based robotic specialization of labor and application of specific picking and collecting capability.

Overall, while it is a small implementation and test, it shows the basic capability of the system to enable a team to perform a function. Given the results, it also shows that the time can be decreased as the actors' capabilities are more efficiently utilized. Showing a trend to greatly utilize the capability of non-human actors in an agricultural collection, validates further investment and basic economic promise to employ robots, in this function.

The next steps are to transition this basic infrastructure to field projects in a realistic agricultural setting. The *HARMS* team will be developed to go into an apple orchard, ground fruit and low plant fruit fields and work to pick fruit, in an actual setting. This test will include more capable robots and more heterogeneous types of robots. The development of the interaction and organization layers of *HARMS* will be included to further the efficiency of the research effort.

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