

Smarter Sharing Is Caring: Weighted Averaging in Decentralized Collective Transport with Obstacle Avoidance

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Abstract

Improved collaboration techniques for tasks executed collectively by multiple agents can lead to increased amount of information available to the agents, increased efficiency of resource utilization, reduced interference among the agents, and faster task completion. An example of a multiagent task that benefits from collaboration is Collective Transport with Obstacle Avoidance: the task of multiple agents jointly moving an object while navigating around obstacles. We propose a new approach to sharing and aggregation of information among the transporting agents that entails (1) considering all available information instead of only their own most pressing concerns through establishing objectively valued system needs and (2) being persuadable instead of stubborn, through assessing how these needs compare to the needs established by their peers. Our system extends and improves upon the work in (Ferrante et al. 2013), leading to better informed agents making efficient decisions that cause less inter-agent interference and lead to faster and more reliable completion of the collective task.

1 Introduction

In many domains, groups of collaborating agents have often exhibited advantages over a single agent through the ability to make better joint decisions and to perform more complex tasks (Sycara 1998; Surowiecki 2004). For this to occur, however, the decision making capabilities of multiple agents and any available data must be combined in sensible ways, allowing for the group to behave as a complex intelligent unit. In this work, we focus on agent collaboration strategies in the decentralized Collective Transport (CT) domain and propose several improvements to the way information and agent opinions have been previously aggregated for CT. We test our improvements against an alternative negotiation strategy proposed in (Ferrante et al. 2013).

An example application for a collaborative Multi-Agent System (MAS) is CT: the task of multiple agents jointly moving an object. Collaboration is necessary when an item is too large, unwieldy, or otherwise impossible to move by a single agent. Furthermore, collaboration can also be beneficial even in domains where a single agent is physically capable of performing the transporting task, but may struggle to do

so adequately, such as when the transported object obscures the agent's view.

While this problem has sometimes been tackled by centralized leader-follower based approaches (Stilwell and Bay 1993; Kosuge et al. 1998; Wang et al. 2004), of particular interest to us is the task of decentralized CT with limited communication, as it necessitates effective agent coordination. The existing decentralized strategies have largely been proposed for and tested on CT in obstacle-free environments, e.g. (Donald, Jennings, and Rus 1997; Yamada and Saito 2001; Campo et al. 2006; Groß and Dorigo 2009), while (Ferrante et al. 2013) tackled CT combined with Obstacle Avoidance (OA) similar to the task of OA by a group of physically connected agents addressed in (Trianni and Dorigo 2006) and (Baldassarre, Parisi, and Nolfi 2006). We aim to improve existing collaboration techniques for the CT domain and use the method described in (Ferrante et al. 2013) as our baseline since, to our knowledge, it is the only existing approach to decentralized coordination for CT with OA.

In (Ferrante et al. 2013), the authors employ “stubborn” and “social” agent behaviors: when an agent detects the goal or any obstacles, the agent will form a goal-approaching or an obstacle-avoiding movement preference, set its state to “stubborn”, pass its preference to its peers (agents within its line of sight), and execute a move according to the communicated preference. Alternatively, if the agent's sensors detect no goal or obstacles, its state will be set to “social”, peers will be notified of this fact, it will average the preferences obtained from its peers, and then move in this averaged direction. Each heading preference is an angle representing the agent's desired deviation from the common environment cue, which was set to be the general direction of the goal, i.e. *goal beacon*. The presented coordination scheme is role-based instead of fully decentralized: the left and right agents located at the rear of the group behave as the left and right wheels located on a joint axis, thus limiting each other's movements. The OA behavior consists of moving in the direction directly opposite to that of the nearest obstacle.

Although in some works in the CT domain agents are allowed to reconfigure themselves by deciding when and how to choose a different spot at which to hold the item (Kube and Bonabeau 2000), in this work we focus on a team with static formation. This means the team can rotate as a whole, but agents cannot change their relative positions to each other nor

to the cargo. While re-gripping capabilities may be generally beneficial for CT, they are excluded from our experiments to allow for a clear assessment of the benefits stemming solely from information processing and propagation.

In *Wisdom of Crowds*, diversity of information, independence of individual judgments, decentralization, and aggregation are listed as the criteria necessary for a “wise” group (Surowiecki 2004). In this work, we propose several behavioral adjustments to collaborative agents through our Weighted-Average CT (W-Avg CT) and test these in the decentralized CT domain. We contend that when making a movement decision, each collaborating agent should consider all information available from its sensors and from its peers, while also balancing being persuasive with being persuadable, which can be accomplished through weighted aggregation. While we believe these behavioral rules can prove beneficial in many domains, here we apply them to the task of a decentralized MAS collectively transporting cargo while avoiding obstacles. We show that the proposed behavioral adjustments improve upon the baseline CT behavior, represented by an MAS employing the negotiation strategy described in (Ferrante et al. 2013).

2 Improvements to Collective Transport

Parting from the baseline approach (Ferrante et al. 2013), we propose increasing the efficiency of CT through allowing agents to prudently consider more information by aggregating data from their individual sensors as well as from each other. We also disallow stubborn behaviors, ensuring that agents can be persuaded by one another according to the objective relative importance of their information. In this section, we describe our motivations for these changes, as well as the details of their implementation for the CT domain.

Agents must attempt to be **prudent**. When choosing a course of action, an agent should take into account all freely available information, even though not all of it might be relevant to said agent’s most pressing current concern. When considering both the data directly related to the current sub-task (such as OA) as well as data that may be helpful for completing the overall task (such as reaching the goal), agents need a way to consolidate the available information sensibly. *Aggregation* approaches deal with combining multiple pieces of data into more concise informative units. Furthermore, weighted aggregation allows placing more or less emphasis on each datum by assigning it a weight. (List 2012b; Tyrrell 1993; Calvo, Mayor, and Mesiar 2002).

In (Ferrante et al. 2013) only the closest obstacle is considered at any given time for establishing the directly opposing OA direction. In our W-Avg CT, we aggregate all obstacle data available to an agent through an averaged weighted sum of the normalized vectors from the agent to each obstacle point detected by its range-finders, producing what we refer to as a *preliminary preference vector*. Each vector is weighted according to its magnitude prior to normalization, with shorter vectors being given more weight since they represent the closest obstacles to be avoided. Algorithm details are provided in figure 1. Note that instead of adding the obstacle collision vectors and rotating the result by 180° , we simply subtract them instead.

Additionally, in (Ferrante et al. 2013), when an agent’s sensors detect nothing, the assigned “social” state dictates that the agent will average the data received from its peers and move according to the outcome, which we call the *final preference*. This causes agents to alternate between the behavior of listening to its peers or “stubborn”ly ignoring their data. While the goal beacon direction is always known, only obstacle data is used if any are sensed by the agent or its peers. When the goal becomes visible, a weighted sum is used to combine the OA and goal approaching directions. Thus, this method does not employ all of the data available at any given time, leading to nearsighted and slower navigation. W-Avg CT is designed to instead consider the obstacles as well as the goal at all times, even when the actual goal is not visible, in which case the beacon direction is used instead.

Prudently considering all available data also implies an agent’s need to be **persuadable** by its peers, since some of this data may come from the peers (in the form of their preliminary vectors). Being “stubborn”, as defined in (Ferrante et al. 2013), results in the agent often ignoring the information available indirectly through its peers. Decision making that disregards the opinions of others in tasks requiring multiple agents can cause livelocks: cycles of looping actions resulting from agent interaction (e.g. the circular ant mill phenomenon) (Jensen and Lesser 2002; Klein and Giese 2004). Larger teams and busier environments are especially susceptible to livelocks, leading to a higher risk of “stubborn”-vs-“stubborn” interference (e.g. if there are walls on both sides of the team, stubbornness can cause a tug-of-war). Allowing agents to objectively evaluate their preferences and compare them to the preferences of their peers can prevent some of the potential pathological behaviors by providing them with the means to individually and intelligently decide which preference should be valued higher.

A more sensible policy would thus require an agent with information to be opinionated but also persuadable, which can again be accomplished through aggregation: an agent’s preliminary preference vector can be added to the preliminary preference vectors transmitted by its peers. In (Ferrante et al. 2013), the system employs minimal communication, consisting of exchanging a single angle with peer agents, i.e. those within direct line of sight. This angle represents the agent’s preferred deviation from a common cue, corresponding to the goal beacon direction and pointing directly upward (for reference, view the map in figure 2). In W-Avg CT, each preliminary preference transmitted by a peer is instead a 2D vector, thus possessing a magnitude in addition to an angle. Since the preliminary preference vector from each peer is obtained by taking into account the distance-based importance of the perceived obstacles, the magnitudes of these preliminary vectors represent the relative importance of the course deviations they represent. As a result, these preliminary peer vectors can be added without any additional weighting, producing the final preference vector which the agent will use to move (figure 1).

Note that only the direction (and not the magnitude) of the final preference vector is considered, as agents travel at constant speed. It should also be noted that although we are

```

SENSING = true //loop: first sense, then act, then sense...
While not at goal, for each simulation step & each agent, do{
  if goal has not been reached {
    if (SENSING)// FORM PRELIMINARY PREFERENCE & NOTIFY PEERS
      if (obstacles are perceived) {
         $\vec{dirOA} = \vec{zerob}$ 
        for each rangefinder hitting an obstacle{
          if (this is the nearest collision)
             $minDistToObstacle = distToCollision$ 
             $weight = 1 - distToCollision/agentVisionRange$ 
             $\vec{dirOA} = \vec{dirCollision}.norm * weight$ 
            //subtract b/c agents move 180° away from obstacles
          }
           $\vec{dirOA} /= obstacleCount$  //averaged
        }
      }
      if (goal is perceived) {
         $\vec{dirGoal} = \vec{zerob}$ 
        for each rangefinder hitting the goal {
           $weight = 1 - distToCollision/agentVisionRange$ 
           $\vec{dirGoal} += (\vec{dirCollision}.norm * weight)$ 
        }
         $\vec{dirGoal} /= goalCount$  //averaged
      }
      if (obstacles perceived AND goal perceived)
         $\vec{preliminaryPref} = (\vec{dirOA} + \vec{dirGoal})/2$ 
      else if (obstacles perceived){ //but not the goal
         $weight = minDistToObstacle/agentVisionRange$ 
         $\vec{dirBeacon} = \vec{dirBeacon}.norm * weight$ 
         $\vec{preliminaryPref} = (\vec{dirOA} + \vec{dirBeacon})/2$ 
      }
      else if (goal perceived)//but not the obstacles
         $\vec{preliminaryPref} = \vec{dirGoal}$ 
      else //no visible obstacles and no visible goal
         $\vec{preliminaryPref} = \text{"Social Marker"}$ 

      send  $\vec{preliminaryPref}$  to peers
      SENSING = false
    }
    else{// ACT: CALCULATE NEW ROTATION AND MOVE
       $sumPrefs = \sum own \& peers' preliminaryPref$ 
      //exclude from sum any "Social Markers", peers' or own
      if everyone sent "Social Markers"
         $newRotation = 0^\circ$  deviation from  $\vec{goalBeacon}$ 
      else
         $newRotation = \angle$  between  $\vec{goalBeacon}$  &  $sumPrefs$ 
         $newDirection = \vec{goalBeacon}$  rotated by  $newRotation^\circ$ 
        move  $stepSpeed$  toward  $newDirection$ 
        SENSING = true
      }
    }
  }
}

```

Figure 1: Weighted-Average Coop. Transport Algorithm

incurring the added cost of transmitting a magnitude along with each preferred deviation angle, taking a single additional value into account can decrease the overall number of inter-agent transmissions needed, due to faster task completion. Additionally, more forward-looking decisions can lead to navigational choices that take longer to become obsolete, potentially allowing for less frequent agent communication.

3 Experimental Setup

In this section, we define and differentiate three approaches for coordinating a team of agents tasked with CT. We also describe the performance metric and the testing environment.

3.1 Tested Systems

To test the proposed modifications for the CT domain, we reimplemented the system presented in (Ferrante et al. 2013) to use as our baseline (Stubborn CT), created a second system for the purpose of assessing the effects of the same approach on a team of “stubborn”-less agents (Social CT), and developed a third system to test the rest of the proposed changes (W-Avg CT). In order to showcase how these com-

pare when coordinating a decentralized group of collaborating agents, we made all three tested systems truly decentralized by removing the role-based aspects present in (Ferrante et al. 2013), allowing all agents to move independently.

Below we briefly define the differences among these approaches, as well as the motivation for testing each one.

1. *Stubborn CT*: a reimplementaion of (Ferrante et al. 2013), modified to be fully decentralized, and used as a baseline. Motivation: to be used as a performance baseline and to test the existing approach on a fully decentralized team.
2. *Social CT*: similar to Stubborn CT, except all agents are “social” (Ferrante et al. 2013) at all times, thus averaging information received from peers with their own. Motivation: to assess the differences between stubbornness and sociability, as well as to diminish the wasteful mutual interference among stubborn agents.
3. *W-Avg CT*: similar to Social CT, except obstacle data is combined through distance-based weighted averaging. Motivation: to improve agents’ information intake and sharing in order to capitalize on the capabilities of a fully collaborative team.

3.2 Performance Metric

Since all three approaches require similarly negligible computation, “time to reach the goal” is not the most informative metric for comparison of the coordination techniques tested in a step-wise simulated environment. Instead, we measure the number of movements it takes to reach the goal (table 1).

Agents are controlled by their internal sense-act loop to best approximate real-world simultaneous action in our simulated environment that processes the agents sequentially; i.e. first each agent senses, then each agent acts, then each senses again, etc. Given that agents have to move every other time step, measuring the number of movements to reach the goal is an adequate metric for comparison. Note that the reported values are per agent, where all agents take an identical number of steps before the team reaches the goal.

Since using a physics engine causes the number of steps to vary slightly among the test runs, the presented values are the averages obtained from 30 runs of each system, along with their respective standard deviations, and success rates indicating in how many of the runs the team successfully made it to the goal instead of getting stuck along the way.

3.3 Testing Environment

The solutions are implemented in C# within a 2D environment on the Unity physics engine (v. 4.5.5f1). All agents are implemented using a single script, thus producing a homogeneous team excepting each agent’s list of peers with whom it can communicate, determined by a line-of-sight of radius $2.0 * agentDiameter$ (measured from agents’ center). Motion is implemented using `AddForce()`, but inertia is eliminated to ensure clear assessment of navigational decisions.

Our tests included a variety of maps designed to establish the capabilities and shortcomings of the approaches. For conciseness, we include results from a single comparatively complex scenario representative of our findings (figure 2).

	vision = $2.0 * agentDiameter$			vision = $1.5 * agentDiameter$		
	Small Cargo Uniform Distr.	Long Cargo Uniform Distr.	Long Cargo Head-Tail Distr.	Small Cargo Uniform Distr.	Long Cargo Uniform Distr.	Long Cargo Head-Tail Distr.
Stubborn	-	-	-	1681.3 (sd:115.9)	-	-
Social	-	-	-	1719.8 (sd:156.3)	-	-
W-Average	408.8 (sd:17.4)	-	950.1 (sd:35.6)	447.5 (sd:18.2)	-	1872.9(sd:140.6)

Table 1: Movements from start to goal: average (st. dev.) with varying vision range, cargo size/shape, and agent distribution. Missing data represents scenarios where the team is never able to reach the goal.

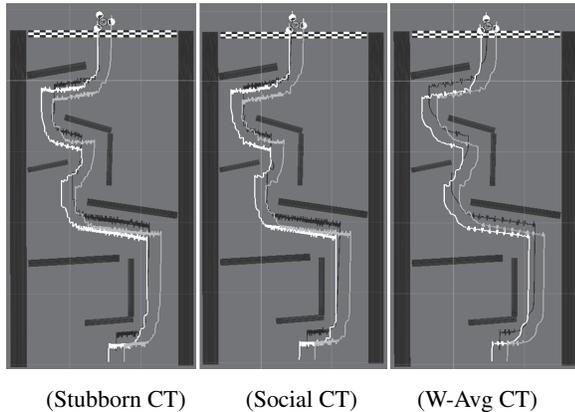


Figure 2: Small-cargo movement trails of the three systems. Each line corresponds to a single agent on the 3-agent team.

While this map is more complex than those used in (Ferrante et al. 2013), it does not require backtracking, as the tested systems are reactive and have no path-planning capabilities.

4 Results & Discussion

To assess the implemented systems, we first test them on a team and cargo similar to those in (Ferrante et al. 2013), repeating each test 30 times to account for variations stemming from the physics engine environment. We then conduct two more experiments with differing agent placement around a more challenging cargo to further test the capabilities, shortcomings, and relative performance of the CT approaches. Results are presented in table 1.

4.1 Small Cargo & Small Team

Our first experiment imitates the setup in (Ferrante et al. 2013): a small cargo transported by a 3-agent team, as depicted in figure 3(a). Agent vision radius is set to $2 * agentDiameter$, counted from an agent's center.

The Stubborn and Social teams are unable to navigate the maze with this vision, while the W-Avg method succeeds consistently, requiring on average 409 steps (table 1, col.1). The cause is the navigational behavior from (Ferrante et al. 2013) employed by the Stubborn and Social approaches. By not taking distance to obstacle into account, OA behavior essentially considers agents to be the size of the area visible to them, as obstacles detected at any distance result in identical

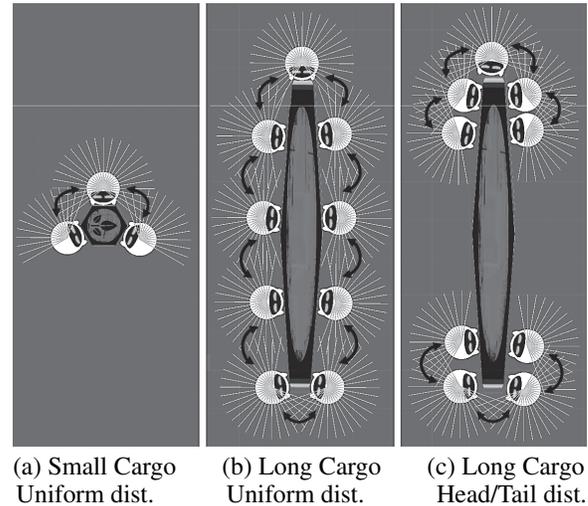


Figure 3: Agent, positioning, peer relations, sensors, & cargo. White agents surround a hexagonal cargo; gray lines are the rangefinder-vision; black arrows depict peer communication.

push away responses. Consequently, Stubborn and Social teams get stuck, never reaching the goal. Note that having blind spots (regions without range-finders in figure 3(a)) may allow teams to navigate tight areas by chance rotation.

To provide a more detailed view of how the approaches compare, agent vision is decreased to $1.5 * agentDiameter$, with peer communication maintained at previous range (table 1, col.4). With decreased vision, Stubborn and Social teams consistently make it to the goal, without any statistically significant difference between them, while W-Avg achieves a much better performance, taking on average 26% of the steps required by the other approaches.

To ground our results, we calculate a free-of-sensing, way-point based estimate of the optimal number of steps needed by the small-cargo team to reach the goal to be 225. As the CT approaches must first sense a wall before deviating from the goal beacon direction, it is natural that the observed performances are not optimal.

4.2 Longer Cargo & Larger Team

To test how the approaches fare in situations with more disparate agent preferences, we conduct a second set of experiments with an elongated, inflexible cargo and a larger team of agents. Given a few agents surrounding a small cargo, there

is limited sensor reading disparity within the team, and thus limited preference disparity, which could simplify the team's task of behaving as a coherent single unit. A longer object allows the task to be assigned to a larger team, with the potential for agents to be located further away from one another. Given the additional space available around the longer cargo, we can also analyze the effects of agent distribution around the object. Below we compare the effects of a uniform and head/tail agent distributions around an elongated cargo.

Since much of the agents' view is obstructed by the long cargo, we remove explicit blind-spots via full 360° agent vision (figures 3(b)&(c)). Both vision ranges are tested and results are presented in table 1. Note that this scenario complicates CT through decreased object maneuverability. We omit the longer cargo way-point based optimum because calculating it is not trivial: pivoting behavior must be implemented, since simply following waypoints gets the team stuck.

Uniform Distribution For the uniformly-distributed agent team test, we position 9 agents around the long cargo, as depicted in figure 3(b). Results are provided in table 1, col.2&5.

None of the approaches are able to complete the task given a uniform agent distribution, which is explained by the way information propagates through the team. Consider a line of agents A-B-C-D-E, where dashes represent peer communication. If edge agents A and E sense obstacles, their peers B and D will take this information into account when forming their final preferences. Central agent C, however, will receive only social opinions from its peers B and D, which don't actually sense anything. As a result, this uninformed central agent will choose to move directly toward the goal beacon, potentially interfering with the movements chosen by the informed agents A, B, D, and E. In this way, having more agents in more areas of the transported cargo may in fact be detrimental to performance under current CT methodologies.

Head-Tail Distribution For the head-tail distributed team test, we position 5 agents at the front and 4 agents at the back of the long cargo, depicted in figure 3(c). Results are presented in table 1, col.3&6.

The head-tail distributed team is significantly affected by the choice of vision range. The smaller vision complicates the task considerably given the cargo length, producing near-sighted behavior in all systems, ultimately leading the Stubborn and Social teams to consistently fail to reach the goal. W-Average team succeeds in all trials, averaging 1873 steps due to the extra pivoting and maneuvering required to transport the long cargo. Having a larger vision range, however, allows the teams to begin turning sooner, which is valuable in the long-cargo scenario. With increased vision, the W-Average team completes the task in half the time required given shorter vision, averaging 950 steps. Stubborn and Social CT are hindered by increased vision (for the reasons discussed earlier) and unable to complete the task once again.

While vision range did not affect performance with uniform agent distribution, we believe head-tail distribution fails differently for two reasons: (1) agents are positioned closely to each other, and thus sensor-disparity is present among the groups (head-group and tail-group) but not within the groups; (2) having an area devoid of agents creates blind-spots that

allow pivoting near walls and making tight turns.

Since the head-tail distributed team outperforms the uniformly distributed team, we see that having uninformed agents can be worse than having fewer agents. A related aspect is the evaluation of agents' position around the cargo. Consider that applying a force toward an end of a long object produces a larger torque than doing so at its center. On the other hand, relocating the center of the cargo is substantially different from rotating it by pushing one end. Consequently, it may be necessary to further weight agent opinions by taking into account their position around the cargo, as well as the specifics of the cargo shape. These investigations should make use of the existing research regarding agent repositioning around a cargo, such as (Kube and Bonabeau 2000).

One way to ensure that agents at key locations are never left uninformed is to increase communication range. Another solution is radial peer communication, which would allow agents to communicate across the cargo or even around an obstacle. This allows for some interesting dynamics, since navigational adjustments of the entire collective are the result of the collaboration of small agent neighborhoods (groups of communicating peers) formed on the perimeter of the cargo.

4.3 Additional Observations

It is apparent that the W-Avg CT approach outperforms the other two, and that the "stubborn" agent behaviors in the Stubborn CT do not offer a statistically significant advantage over a fully cooperative Social CT team. In this section, we further discuss the behavioral differences of these approaches.

Although the W-Avg approach does not achieve optimal time-step efficiency, not only does it outperform the other approaches, but it is also considerably closer to the optimum behavior than it is to its Social and Stubborn counterparts. Its inability to reach the optimum is explained by the simplistic OA behavior (presented in (Ferrante et al. 2013) and implemented here) that ultimately causes agents to move along walls in ascending triangle formation. Not only is this type of back and forth movement wasteful, it also causes agents to always navigate upward along an obstacle even when navigating downward would result in a shorter path to the goal, or to even get stuck behind obstacles perpendicular to the direction of the goal beacon, in cul-de-sacs (which require the team to move away from the goal in order to advance), or in "doorways" (where agents' preferences could cancel out).

The behavioral differences of the systems can be seen in figure 2. The lines correspond to the paths taken by each of the three agents in the small-cargo scenario, chosen for clarity as the larger teams create busier paths. Note the differences in line width resulting from the number of movements per section of the path. It is clear that the Stubborn and Social approaches make decisions with shorter term usefulness, requiring more adjustments along the way, and resulting in more jagged and busier paths than those of W-Avg CT.

If a team employed all-to-all communication, then a Stubborn system would behave similarly to a W-Avg system, with the former averaging the preferences through physical movement, and the latter averaging them mathematically and moving after. Nevertheless, an added benefit of mathematical averaging is a decrease in wasted effort. For example, if all

agents wish to go in directly opposing directions, a stubborn team will waste effort and incur wear and tear on the system while fighting agent interference. A W-Avg team will instead determine which resistances are futile and only produce part of the originally intended movements, thus decreasing unnecessary physical work in the system.

5 Conclusions

In this work, we devise and test improvements for coordinating collaborative agents in the domain of CT with OA. Experimentally, we show that the proposed changes are beneficial to a team's performance. These improvements revolve around the following agent characteristics: (1) collaborative agents should be prudent in their data assessments, taking into account all available information and combining it in a sensible manner intended to value the team's short- and long-term goals; (2) agents should be persuadable by their peers, as stubbornness ignores potentially valuable information.

It is evident that aggregation is as instrumental for successful CT as it is for many other domains, e.g. (Riggs and Wu 2012; List 2012a; Wang, Yang, and Xu 2005; Major and Ragsdale 2000; Conradt and Roper 2005). However, as showcased by the failed experiments and discussed pathologies of simplistic the OA of the three systems, the outcome also largely depends on how agents perceive and process their environment. Seeing farther allows detecting more obstacles, but it can also lead to a higher chance of inter-agent interference. Without taking distance to obstacles into account, the walls closest to any one agent are all equally import, making it difficult to make team-wide smart navigational choices. With 360° sensor range, the walls left behind are still detected, so taking the goal-beacon into account is instrumental in avoiding getting stuck.

Despite having achieved better performance than the only other known to us approach for decentralized CT with OA (Ferrante et al. 2013), it is clear that there is much room left for improvement. Since aggregation is a highly malleable approach, as we learn more about how to interpret, share, and rate the importance of data, we can incorporate these new insights, further improving CT behavior.

References

Baldassarre, G.; Parisi, D.; and Nolfi, S. 2006. Distributed coordination of simulated robots based on self-organization. *Artificial Life* 12(3):289–311.

Calvo, T.; Mayor, G.; and Mesiar, R. 2002. *Aggregation Operators: New Trends and Applications*. Studies in Fuzziness and Soft Computing. Physica-Verlag HD.

Campo, A.; Nouyan, S.; Birattari, M.; Groß, R.; and Dorigo, M. 2006. Negotiation of goal direction for cooperative transport. In *Ant Colony Optimization & Swarm Intell.* Springer. 191–202.

Conradt, L., and Roper, T. J. 2005. Consensus decision making in animals. *Trends in Ecology & Evolution* 20(8):449–456.

Donald, B. R.; Jennings, J.; and Rus, D. 1997. Information invariants for distributed manipulation. *The International Journal of Robotics Research* 16(5):673–702.

Ferrante, E.; Brambilla, M.; Birattari, M.; and Dorigo, M. 2013. Socially-mediated negotiation for obstacle avoidance in collec-

tive transport. In *Distributed Autonomous Robotic Systems*. Springer. 571–583.

Groß, R., and Dorigo, M. 2009. Towards group transport by swarms of robots. *Int. J. Bio-Inspired Computation* 1(1/2):1–13.

Jensen, D., and Lesser, V. 2002. Social pathologies of adaptive agents. In *Safe Learning Agents: Papers from the 2002 AAAI Spring Symposium*, 13–19. AAAI Press.

Klein, F., and Giese, H. 2004. Separation of concerns for mechatronic multi-agent systems through dynamic communities. In *Software Engineering for Multi-Agent Systems III*. Springer. 272–289.

Kosuge, K.; Oosumi, T.; Satou, M.; Chiba, K.; and Takeo, K. 1998. Transportation of a single object by two decentralized-controlled nonholonomic mobile robots. In *Proc. IEEE International Conference on Robotics and Automation*, volume 4, 2989–2994.

Kube, C. R., and Bonabeau, E. 2000. Cooperative transport by ants and robots. *Robotics and Autonomous Systems* 30(1):85–101.

List, C. 2012a. Collective wisdom: lessons from the theory of judgment aggregation. In Landemore, H., and Elster, J., eds., *Collective Wisdom: Principles and Mechanisms*. Cambridge University Press.

List, C. 2012b. The theory of judgment aggregation: An introductory review. *Synthese* 187(1):179–207.

Major, R. L., and Ragsdale, C. T. 2000. An aggregation approach to the classification problem using multiple prediction experts. *Information processing & management* 36(4):683–696.

Riggs, C., and Wu, A. S. 2012. Variation as an element in multi-agent control for target tracking. In *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, 834–841. IEEE.

Stilwell, D. J., and Bay, J. S. 1993. Toward the development of a material transport system using swarms of ant-like robots. In *Proc. IEEE International Conf. Robotics and Automation*, 766–771.

Surowiecki, J. 2004. *The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies, and Nations*. Doubleday.

Sycara, K. P. 1998. Multiagent systems. *AI magazine* 19(2):79.

Trianni, V., and Dorigo, M. 2006. Self-organisation and communication in groups of simulated and physical robots. *Biological Cybernetics* 95(3):213–231.

Tyrrell, T. 1993. *Computational Mechanisms for Action Selection*. University of Edinburgh.

Wang, Z.-D.; Takano, Y.; Hirata, Y.; and Kosuge, K. 2004. A pushing leader based decentralized control method for cooperative object transportation. In *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 1, 1035–1040.

Wang, Y.-M.; Yang, J.-B.; and Xu, D.-L. 2005. A preference aggregation method through the estimation of utility intervals. *Computers & Operations Research* 32(8):2027–2049.

Yamada, S., and Saito, J. 2001. Adaptive action selection without explicit communication for multirobot box-pushing. *IEEE Trans. Systems, Man, and Cybernetics, Part C: Applications and Reviews* 31(3):398–404.