Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Assistive Formation Maintenance for Human-Led Multi-Robot Systems

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***Abstract*—In ground-based military maneuvers, group formations require flexibility when traversing from one point to the next. For a human-led team of semi-autonomous agents, a certain level of awareness demonstrated by the agents regarding the quality of the formation is preferable. Through the use of a Multi-Robot System (MRS), this work combines leader-follower principles augmented by an assistive formation maintenance (AFM) method to improve formation keeping and demonstrate a formation-in-motion concept. This is achieved using the Robot Mean Task Allocation method (RTMA), a strategy used to allocate formation positions to each unit within a continuously mobile MRS. The end goal is to provide a military application that allows a soldier to efficiently tele-operate a semi-autonomous MRS capable of holding formation amidst a cluttered environment. Baseline simulation is performed in Player/Stage to show the applicability of our developed model and its potential for expansive research.**

***Index Terms*—Multi-Robot Systems (MRS), Assistive Formation Maintenance (AFM), Robot-Task Mean Allocation Algorithm (RTMA)**

I. Introduction

In an effort to leverage the benefits of advancing robotic technology, it is estimated that by 2015, one-third of military vehicles will be unmanned [1]. Of the many looming concerns, a primary interest will be determining which control schemes best assist the military in accomplishing its objectives. This change in demographic on the battlefield is in response to a need to preserve the lives of human soldiers, specifically those whose talents could be better put to use elsewhere in war. One outlet for such talents is for soldiers to serve as the human component in a tele-operated multi-robot system (MRS). A uniform set of semi-autonomous ground vehicles commanded by a soldier would greatly enhance the military's flexibility for a range of high-risk scenarios. The objective of the proposed work is to investigate the limitations in formation-keeping for a human-led team of semi-autonomous unmanned ground vehicles (UGV).

In ground-based military maneuvers, mobile teams must retain their formation consistently when traversing from one waypoint to another for different purposes. Whether establishing a required configuration for efficient communication or to serve as convoy protection, maintaining formation can reduce potential threats to the system. For a human-led team, a certain level of awareness demonstrated by the agents regarding the quality of the formation is preferable. It is acheiving this goal of awareness that will move the topic of formation maintenance beyond current state-of-the-art techniques. Furthermore, this reduces the cognitive workload of the human leader, a major advantage in high-stress scenarios such as combat. This work considers an MRS "platoon" designed to arrange autonomously into predefined military formations (i.e. row, v, column, echelon, customized, etc.) while collectively moving in a specific direction. Given hostile territory (modeled as a cluttered environment), a set of rules must be in place to make decisions regarding 1) the instantaneous positions of each unit during formation and 2) the tele-operator's role in controlling the platoon's direction. The latter will be considered future work while the former will be addressed in this paper.

The task of navigating in a cluttered environment can be cumbersome and even more so when attempting to maneuver as a part of a formation. Consider a follower forced to negotiate an obstacle during motion, temporarily unable to maintain close proximity to its goal position in the formation. Enabling the remaining team members to dynamically reassess what other available followers can trade assignments contributes to factors such as reducing time out of formation and improving situational awareness of the team. Our concern is combining leader-follower principles with the AFM method to define a formation-in-motion concept. Greater flexibility in testing a number of system parameters (i.e. number of agents, types of obstacles, formation velocity, etc.) also validates the use of this unique system design.

II. Background

MRS formation control and the formation-keeping problem have been addressed in many different ways. Certain research conducted makes use of leader-follower paradigms while others focus on the principles of the potential field method and customized control laws. Work by Mesbahi et al. [2] is founded in a time-varying directed leader-follower graph where dependence is introduced between leader-follower pairs. Highly theoretical, the work's most relevant application is geared towards orbiting spacecraft. Additional techniques are investigated in [2] where sensor-specific geometric analysis is performed to govern multi-agent formation. In [3–9], the consistent theme behind the researchers' leader-follower control strategies is the aim to designate a particular reference frame in the formation and control the remaining frames with respect to that reference. Since our work considers a human-led MRS, a dedicated leader model is needed. Therefore, similarly, the work presented here defines a single leader and all remaining followers establish their own global position in the world relative to that leader.

In addition to leader-follower schema found in literature, potential field methods and formal control laws are also considered by those doing work in MRS. Schneider et al. [10] addresses the benefits of sensor and communication networks and considers the variable strictness in formation maintenance. Their work assigns formation, obstacle and goal forces to cause each agent in the system to converge to a certain target point. While this is stable in theory, unaccounted for is a higher level of autonomy and group coordination. Li and Chen [8] introduce the application of an adaptive neural network to enable an MRS to avoid two distinct obstacle types, allowing leader-follower role switching as well as formation switching. Though useful for continuously adaptive systems, our interest is in consistent maintenance of a specified formation, keeping the formation chosen as the highest priority. Brock et al. [11] investigates the formation keeping problem by providing a custom set of conditions for low-level control of each agent, while in motion, to address formation maintenance. To the authors' knowledge, there have been no attempts to apply task allocation solutions for formation keeping problems, which this work addresses directly. Several formations are tested independently to prove the value of allowing each agent in the formation to compensate for one or more agents forced to negotiate obstacles in their local environment. This has led to the development of the AFM method.

III. Multi-Agent Formation Control

The work presented in this paper relies on a traditional behavior switching method whereby an agent will converge to its respective goal position (tracking) during motion, but when negotiating clutter (obstacle avoidance), the team collectively re-evaluates the position assignments. This allows the system to react more immediately to unknown changes in the environment for the explicit purpose of maintaining formation. Often times, a platoon will need to secure an area of foreign terrain. With this system, the MRS can be tele-operated remotely to move with and protect a group of soldiers (i.e. using different formations) or perform other duties in the vicinity, depending on the need. Changes in a given military mission will require such a real-time capability. The end goal will be to implement this system in a decentralized way, thus posing two interesting questions: 1) How can you measure the utility of assigning an agent a place in the mobile formation? 2) If the positions of the agents are changing over time due to a group migration, what type(s) of behaviors can best accommodate the position assignment scheme amidst a cluttered environment?

For this work we consider the scenario of an MRS instructed to arrange into different military formations headed due north. The leader assumes a location at the forefront of the formation, while the position of the remaining units has yet to be determined (see Figure 1). The only inputs considered for our system are the leader's position and a task list of locations for remaining agents outlining a specific military formation. These locations (or tasks) are calculated with respect to the leader's position.

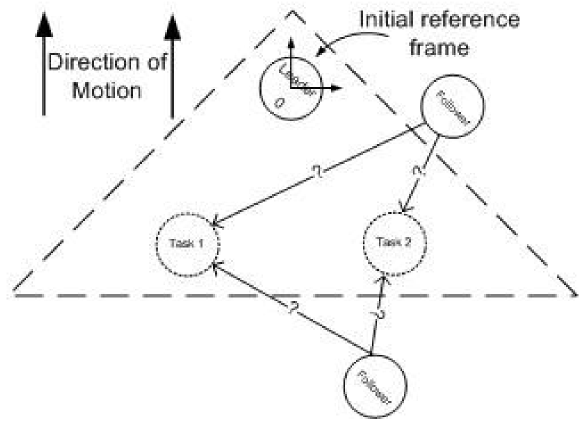

Fig. 1. Formation task allocation scenario

A. Task Allocation

Depending on the deployment method used to insert the MRS into the environment of interest, there is no guarantee that the initial collective arrangement will resemble the desired formation. Therefore, during navigation, the MRS must arrange into its initial formation. The "leader" assignment at t_0 is predetermined and it is presumed that the agent chosen as leader will provide the system reference frame from which subsequent follower formation positions will be derived.

The selection process determining which "follower" should be positioned at which location with respect to the leader can be modeled as a task allocation problem. The Robot Task Mean Allocation (RTMA) algorithm [12] makes use of our system parameters and provides a useful way to select the most suitable formation position for each follower. The RTMA algorithm is a combination of two other task allocation algorithms designed to minimize the obtrusiveness in traditional market-based approaches. While it is used to address our initial formation problem, the work was originally developed as a decision-aid for robots that had won two competing tasks in an auction. By combining a new utility function with a new way for a robot to select between competing task assignments, RTMA emerged. For a large MRS, this technique reduces the number of communication messages required for transmission. The method is governed by Equations 1 and 2.

$$C(R_w, T_i) = \sum_{k=1}^{M} \frac{D(R_k, T_i)}{M} - D(R_w, T_i) \tag{1}$$

$$C(R_w, T_i) > C(R_w, T_j) \tag{2}$$

For M robots, the utility, C, for a given robot, R_w, to reach a given task location, T_i, is defined as the average distance from all robots to task T_i less the distance, D, from R_w to T_i. Here, robot R_w will select task T_i instead of task T_j *iff*

$$C(r,t) = \begin{bmatrix} C_{11} & C_{12} & C_{1j} & C_{1(M-1)} & C_{1M} \\ C_{21} & . & .. & \dots & C_{2M} \\ C_{w1} & .. & C_{wj} & .. & C_{3M} \\ C_{(M-1)1} & \dots & .. & . & C_{(M-1)M} \\ C_{M1} & C_{M2} & C_{Mj} & C_{M(M-1)} & C_{MM} \end{bmatrix}$$

Fig. 2. Utility-decision matrix

the condition in Equation 2 is met. Since the RTMA scheme is based on distances to a task (i.e. goal), it is a suitable choice for a mobile MRS navigating from one point to another. Instead of selecting between two competing tasks, however, we employ the use of RTMA as though all M agents must decide between all M competing tasks. All position locations for a given formation, therefore, are considered "competing tasks" that must be auctioned off to each agent in the MRS. As a result, a utility vector for all tasks is assigned for each robot resulting in a utility-decision matrix, shown in Figure 2.

Here, for a given robot, r, the row of each column represents the utility robot r would incur for each task, t. The following algorithm is used to cycle through C and select the maximum utility appropriate for each robot.

1) Locate the maximum utility value in C, q.
2) Obtain indicies [r,t] of q.
3) Assign robot r task t.
4) Remove row r and column t from C.
5) Repeat (1-4) until all robots are assigned a task.

Once the formation positions have been assigned as short-term goals for each follower, how each agent successfully navigates towards that goal must be addressed.

B. Tracking and Mobilization

In this work, the system will maintain a dedicated leader, that is, the leader will not be considered a member of the specified formation. For an MRS of M units, the leader-follower structure is controlled in two stages. First, the leader's next position is estimated at time step $N+1$ (Equation 3) according to velocity and heading constants. Next, the $N+1$ position of each follower is calculated with respect to the leader based on its predetermined position within the formation (Equation 4). These next-state positions calculated provide the information used in the RTMA task allocation method described earlier. Finally, followers track these continually updated next state task assignments.

$$(X_{L_{n+1}}, Y_{L_{n+1}}) = (X_{L_n}, Y_{L_n}) + V_{Leader} * (\cos(\alpha), \sin(\alpha)) * dt \quad (3)$$

$$(X_{F_{n+1}}, Y_{F_{n+1}}) = R * (\cos(\theta), \sin(\theta)) + (X_{L_{n+1}}, Y_{L_{n+1}}) \quad (4)$$

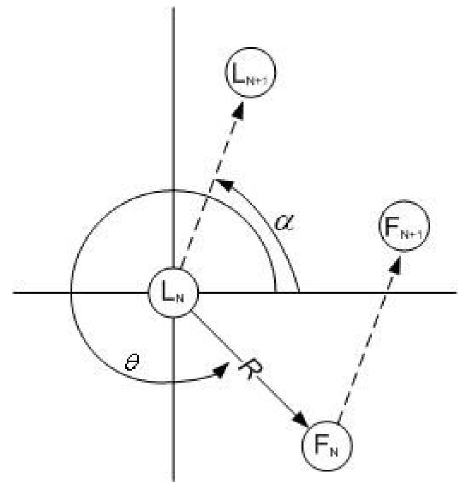

Fig. 3. Leader-follower relationship

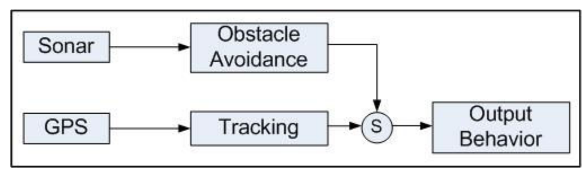

Fig. 4. Basic subsumption system architecture

C. Obstacle Avoidance

Presuming the path of the leader is not impeded during forward motion, the remaining units, as followers, must sustain the formation while avoiding obstacles. The obstacle avoidance behavior presented operates as a function of the angular relationship between a given follower's current heading and its heading relative to the nearest obstacle detected. An average of sonar measurements along with a discrete set of angle options are used to re-direct a follower left or right of the detected impedance allowing the unit to remain clear of the detected obstacle. This obstacle avoidance algorithm proved sufficient to test within the framework of the scenario considered, however, more effecient algorithms could have been implemented. A simplistic subsumption architecture diagram is provided in Figure 4 to illustrate the behaviors available.

D. Position Switching

Though this work is grounded in a leader-follower structure, the scope of the leader's relationship to its followers does not extend beyond serving as a continuous reference frame for others in the formation. For the followers, two questions drive the use of position switching via task allocation methods:

1) Which of the followers in the formation is not also impeded by an obstacle?
2) Which of the followers is available to assume a more suitable position in the formation relative to the rest of the units?

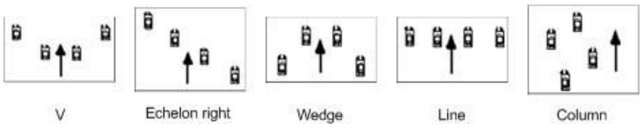

Fig. 5. Military formations

Based on this implementation, an alternative next-state set of assignments can be chosen, thus improving the quality of maintaining a consistent formation. It is worth mentioning that a problem may result if the width of the formation is more than an order of magnitude smaller than the impeding obstacle width. In this case, the system may continuously switch task assignments between units without ever successfully moving beyond the obstacle. Here, the role of the tele-operator will aid in preventing this type of chatter between behaviors.

IV. Results

A. Set-up

Using Player/Stage [13], a simulation experiment was set up to test the various formations navigating in a common environment. We considered five formations ("V", "echelon", "wedge", "line", "column") as derived from [14] such that the leader was considered external to the formation and only provided the frame of reference for global positioning. Each simulation consisted of a single pioneer equipped with a 180 degrees field of view SICK laser range finder. Additionally, 4 amigobot robots were equipped with 8 sonar sensors, each with a range of 3 [m] and 30 degrees field of view and overlapping by 15 degrees. The pioneer's velocity was set constant at 0.3 [m/s] while the amigobots were controlled with a variable velocity scheme defined as a function of distance to their task and obstacle presence. Velocities of the follower units fell in the range of 0.1 – 0.3 [m/s]. The pioneer travels a total of 25 [m] for each trial, while the remaining units attempt to achieve and maintain formation. Figures 5 and 6 show the different military formations considered and the "V" formation in the Stage simulator, respectively. For all trials conducted, the formation is assigned a heading of 90 degrees to maintain simplicity.

At each time step, each unit executes a tracking behavior to keep track of its assigned task within the formation. When one unit indicates that it has switched behaviors in order avoid an obstacle, the system re-evaluates each unit's suitability for their current task relative to the newly available tasks that may be more easily filled. Figure 7 visually depicts the transition from an initial task assignment set to another as a result of encountering an obstacle.

B. Measurements

For each formation, we evaluated the benefit of incorporating the AFM method while negotiating obstacles. This was accomplished by considering the following average measured data, S, of each formation: total distance traveled, percentage of time spent avoiding obstacles, and total excess distance traveled during obstacle avoidance. Additionally, there were

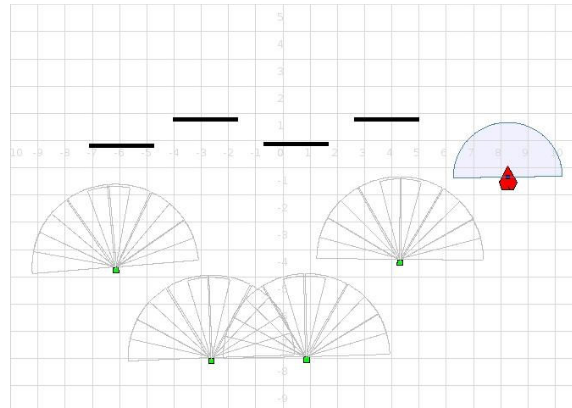

Fig. 6. V formation approaching obstacle field

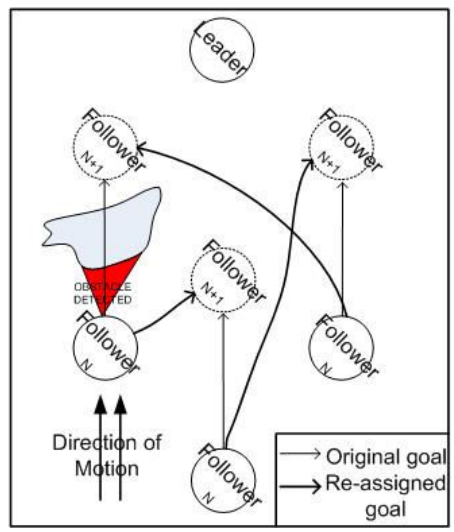

Fig. 7. Task assignment transition

qualitative results obtained through observation, not apparent in the presented data. A comparison of each formation's performance with AFM (task switching enabled) and without AFM (task switching disabled) is summarized in Table I using differences of average values. A total of 60 trials were run for each formation (i.e. 30 w/AFM, 30 w/o AFM) and each trial lasted approximately 1.5 minutes each.

C. Observations

After averaging the collected data, (see Section IV-B), for each formation and for each measurement, we compute the difference of these average values for formations with AFM and those without AFM. Instead of evaluating the performance of each unit, it is more useful to evaluate the performance of the formation as a whole, thus the difference values for all units in the formation are summed to provide a collective evaluation metric. Equation 5 explicitly defines how the values in Table I are calculated.

TABLE I
SUMMARY OF FORMATION PERFORMANCE

Formation	Δ Distance [m]	Δ OA [%]	Δ Excess [m]
V	-0.169	-0.133	-0.407
Echelon	-0.177	-4.4	-0.44
Wedge	7.773	11.2	0.327
Line	-5.32	-8.2	-0.297
Column	0.201	0.8	-0.401

$$\sum_{k=1}^{M} S_{k_{w/AFM}} - S_{k_{wo/AFM}} \tag{5}$$

- S: Average metric (total distance traveled, percentage of time spent avoiding obstacles, and total excess distance traveled during obstacle avoidance)
- K: Each unit in the formation
- M: Total number of units per formation

Any value less than zero listed in Table I indicates a favorable performance when using the AFM method. The most obvious performance improvement was for the "line" formation, traveling 5.32 [m] less and spending 8.2 percent less time avoiding obstacles when using AFM. Additionally, the "echelon" formation spent 4.4 percent less time in obstacle avoidance mode when using AFM. Interesting to note is that although the "line" formation with the AFM method performed better than without, the initial and final task assignments were the same. Therefore, we attribute this improvement to some or all units momentarily being re-assigned to a different task during obstacle avoidance, thus impacting initial change in heading, and due to persistent obstacle presence, eventually reverting to their original task assignments. Though this was not quantified, it will be addressed in the last section. Of the five formations tested, "line" and "echelon" military formations demonstrated the most potential for the use of task re-assignment amidst obstacle avoidance for the purpose of formation maintenance.

Several factors contributed to the results for the "V", "wedge", and "column" formations. The size and arrangement of the obstacles within the environment combined with how task re-assignment was implemented limited the maneuverability of the team in those formations. For example, if a task re-assignment was made due to the most forward-positioned unit encountering an obstacle, all units re-arranged prematurely without accounting for whether or not the new assignment would eventually result in redundant obstacle avoidance moments later. This is a predictive feature that, if implemented correctly, will serve to improve future versions.

Another consideration is the defined distance between task assignments. During initial simulations, it was observed that an excess of task assignment switching took place the more closely the formation positions were defined relative to each other. This excess switching was also due to units frequently mistaking other units for obstacles, thus a suitable distance was chosen relative to the location of true obstacles in the environment to prevent this error. Researching the limits of uniform distance between assignment locations as well as including additional sensing (vision) would also be an improvement to the system.

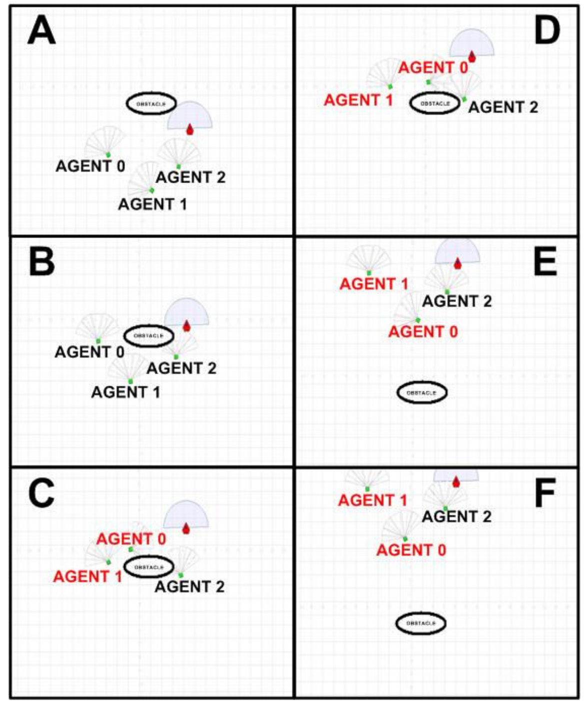

Fig. 8. Periodic snapshots of task re-assignment sequence demonstrated with three agents achieving a "V" formation

Finally for all three formations (based on the conditions of equations 1 and 2), units were rarely significantly hindered by an encountered obstacle enough to warrant a change in task assignment. Therefore, many of the trials for a given formation using the AFM behaved much like those without the AFM. This also explains the negligible difference in data collected, especially for "V" and "column" formations.

Aside from the trials from which data was collected, variations on the experimental set-up previously described were implemented in simulation as well. The diagram in Figure 8 shows how the obstacle avoidance behavior in cooperation with the AFM method leads agents 0 and 1 to exchange formation positions between the pre- and post-obstacle avoidance sequence. The change can be seen upon closer inspection of Figures 8B through 8E. If more agents were to be added, the use of the AFM method may produce an emerging behavior, but we leave that to future work.

V. Conclusions and Future Work

This preliminary research combines leader-follower and task allocation methodologies to produce a multi-agent system equipped with additional information when navigating in a cluttered terrain. As mentioned in the previous section, based on the utility function in Equation 1, the likelihood of task switching taking place is affected by the size of the environment relative to the size of the formation and the impact of the impeding obstacles. Determining that relationship of formation size to environment and possible requirements necessary to ensure successful task switching is worth investigating.

Also alluded to earlier, using recently acquired knowledge about the environment to influence or predict the benefit of one unit switching task assignments with another is a topic of interest for this work. Most immediate, however, is the effort to develop a method for quantifying how often task switching takes place during obstacle avoidance to better explain the results obtained in the previous section. Once the AFM method is confirmed as a valid tool for task switching of a continuously mobile MRS, comparison to traditional market-based task allocation algorithms will be warranted as well. Enhancements to the current simulation and actual hardware implementation of the AFM method are planned for subsequent validation of this research.

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