# Distributed Coordinated Mobile Sensor Control Target Tracking in Multiple Wireless Sensor Networks

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**Abstract:** Wireless Sensor Networks (WSNs) is highly distributed network of small, lightweight wireless nodes. It monitors the environment or system by measuring physical parameters such as temperature, pressure, humidity. A wireless sensor network is a collection of nodes organized into a cooperative network. The existing presented Mobile sensor controller is used to measure the mobile target signal's time of arrival (TOA). It's related to tracking signal-emitting purpose of mobile targets which is used to navigated mobile sensors based on signal reception. Mobile target's position is unknown so that they acquire from TOA. Both the mobile target and mobile sensor are used to estimate their locations before they directing mobile sensor's movement to follow their target. TOA measurements are easy to acquire the mobile target. However, in Distributed Coordinated Mobile Sensor Control Target Tracking (DCM-SCT) scheme provides the formulation work which is done through the control of multiple cooperating autonomous sensor platforms. The proposed work provides an intelligent mobile sensor platform with high level of state information to the behavior-based mobile target tracking control system. Sensors are considered as autonomous agents and sensor motion control are based on gradient control trace with the target helps to reduce tracking error. Multiple objective functions are allows to reactive control in complex environments with multiple constraints. Simulations were conducted to measure the performance of in terms of DCM-SCT which has Location privacy level, Number of latency per packets, delivery rate, average end to end delay and control packets.

Keywords: DCM-SCT, Delivery rate, Mobile sensor, Mobile target, Time of arrival

#### 1. Introduction

A wireless sensor network (WSN) consists of spatially distributed autonomous sensors to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and to cooperatively pass their data through the network to a main location. The more modern networks are bi-directional, also enabling control of sensor activity. A wireless sensor network (WSN) is a wireless network consisting of spatially distributed autonomous devices using sensors to monitor physical or environmental conditions. A WSN system incorporates a gateway that provides wireless connectivity back to the wired world and distributed nodes. The emerging field of wireless sensor networks combines sensing, computation, and communication into a single tiny device. The power of wireless sensor networks lies in the ability to deploy large numbers of tiny nodes that assemble and configure themselves.





In Distributed Coordinated Mobile Sensor Control Target Tracking (DCM-SCT)scheme for mobile wireless sensor networks has formulates the control of multiple cooperating autonomous sensor platforms. The distributed sensor allows to view simultaneous vantage points from the multiple access and creating significant processing gain from the spatial diversity. Distributed sensors give an immediate solution of the target position. It provides an adaptive and cooperative control of the mobile sensor platforms in the mobile sensor target. Intelligent mobile sensor provides high level state information to behavior-based mobile target tracking control system. The multiple objective functions allow the mobile sensor tracking to reactive the control in complex environments with multiple constraints.

The mobile sensor provides distributed sensor-target assignment that used to sense the motion control of sensor. Sensors are considered as autonomous agents and their objective function of each sensor concentrates on the tracking accuracy and tracking cost. In mobile sensor, the sensor motion control are based on gradient control trace which has the target to reduce tracking error in the system. The advantage of the distributed coordinated mobile sensor target scheme has cooperation of multiple sensor platforms. It increases the efficiency of target tracking in distributed environment and leads in effective for 2-D target tracking application system. Potential synergy on mobile sensor target tracking which comes less computational cost and communication energy.

## 2. Literature Review

Controlling the behavior of a robot or autonomous vehicle [1] in a stochastic, complex environment is a formidable challenge in artificial intelligence. In stochastic domains, both the current state of the vehicle and the environment are typically reconsidered before deciding each action. If the domain is simple enough, effective plans can be encoded by predetermining the best vehicle action for all possible contingencies, or in all possible vehicle states. In complex environments, particularly with other vehicles, the explosion of possible contingencies or vehicle states prohibits this. In these cases, behavior-based architectures are often employed, with each behavior focused on a specialized vehicle. Objective overall vehicle behavior relies heavily on the proper combination, or arbitration, of individual behaviors.

The accuracy of 3D position [2] estimation using two angles-only sensors (such as passive optical imagers) is investigated. Beginning with the basic multi-sensor triangulation equations used to estimate a 3D target position, error propagation equations are derived by taking the appropriate partial derivatives with respect to various measurement errors. Next the concept of gaussian measurement error is introduced and used to relate the standard deviation of various measurement errors to the standard deviation of the target 3D position estimate. Plots of the various error propagation coefficients are generated. These analytical results are verified using a Monte-Carlo statistical approach. The result is a set of equations and graphs useful for designing a two-sensor system to meet a required accuracy specification. Triangulation can be performed using multiple sensors at known locations to determine the location of a fixed or moving object, or it can be performed using a moving sensor (observing a stationary target) to create a virtual baseline over time. The technique of interest in this paper is triangulation between two sensors.

An innovative architecture for real-time adaptive [3] and cooperative control of autonomous sensor platforms in a marine sensor network is described in the context of the autonomous oceanographic network scenario. This architecture has three major components, an intelligent, logical sensor that provides high-level environmental state information to a behavior-based autonomous vehicle control system, a new approach to behavior-based control of autonomous vehicles using multiple objective functions that allows reactive control in complex environments with multiple constraints, and an approach to cooperative robotics that is a hybrid between the swarm cooperation and intentional cooperation approaches. The mobility of the sensor platforms is a key advantage of this strategy, allowing dynamic optimization of the sensor locations with respect to the classification or localization of a process of interest including processes which can be time varying, not spatially isotropic and for which action is required in real-time. Experimental results are presented for a 2-D target tracking application in which fully autonomous surface craft using simulated bearing sensors acquired.

An autonomous operation of unmanned marine vehicles in accordance [4] with convention for safe and proper collision avoidance as prescribed by the Coast Guard Collision Regulations (COLREGS). These rules are written to train and guide safe human operation of marine vehicles and are heavily dependent on human common sense in determining rule applicability as well as rule execution, especially when multiple rules apply simultaneously. To capture the flexibility exploited by humans, this work applies a novel method of multi-objective optimization, interval programming, in a behavior-based control framework for representing the navigation rules, as well as task behaviors, in a way that achieves simultaneous optimal satisfaction. We present experimental validation of this approach using multiple autonomous surface craft. This work represents the first in-field demonstration of multi objective optimization applied to autonomous COLREGS-based marine vehicle navigation. Although the COLREGS is a document suitable for guiding human behavior.

In-field operation of two interacting autonomous [5] marine vehicles to demonstrate the suitability of interval programming (IvP), a novel mathematical model for multiple-objective optimization. Broadly speaking, IvP coordinates competing control needs such as primary task execution that depends on a sufficient position estimate and vehicle maneuvers that will improve that position estimate. In this work, vehicles cooperate to improve their position estimates using a sequence of vehicle-to-vehicle range estimates from acoustic modems. Coordinating primary task execution and sensor quality maintenance is a ubiquitous problem, especially in underwater marine vehicles. This work represents the first use of multi objective optimization in a behavior-based architecture to address this problem.

In the behavior-based approach the control [6] of a robot is shared between multiple behaviors with different and possibly incommensurable objectives. In most cases when deciding what next action to take, multiple conflicting objectives should be considered simultaneously. Thus one faces the problem of deciding what next action to select. This is known as the action selection problem and is the primary focus of this dissertation. In particular, two aspects of the action selection problem, that are subject to investigation consist of 1) the formulation of effective mechanisms for coordination of the behaviors' activities into strategies for rational and coherent behavior and 2) the

Volume 6 Issue 5, May 2017 <u>www.ijsr.net</u> Licensed Under Creative Commons Attribution CC BY construction of fault-tolerant behaviors from a multitude of less reliable ones. Regarding the first issue, it is demonstrated that multiple objective decision theory provides a suitable formalism to encompass ideas from behavior-based system synthesis and control.

Architecture is presented in which distributed task achieving [7] modules, or behaviors, cooperatively determine a mobile robots path by voting for each of various possible actions. An arbiter then performs command fusion and selects that action which best satisfies the prioritized goals of the system, as expressed by these votes, without the need to average commands. In order to function in unstructured, unknown, or dynamic

Environments, a mobile robot must be able to perceive its surroundings and generate actions that are appropriate for that environment and for the goals of the robotic system.Mobile robots need to combine information from several different sources. For example, the CMU Navlab vehicles are equipped with sensors such as video cameras, laser rangefinders, sonars, and inertial navigation systems, which are variously used by subsystems that follow roads, track paths, avoid obstacles and rough terrain, seek goals, and perform teleoperation. Because the raw sensor data and the internal representations used by these subsystems tend to vary widely, especially when these modules have been developed independently.

Architecture for controlling mobile [8] robots. Layers of control system are built to let the robot operate at increasing levels of competence. Lavers are made up of asynchronous modules which communicate over low bandwidth channels. Each module is an instance of a fairly simple computational machine. Higher level layers can subsume the roles of lower levels by suppressing their outputs. However, lower levels continue to function as higher levels are added. The result is a robust and flexible robot control system. The system is intended to control a robot that wanders the office areas of our laboratory, building maps of its surroundings. In this paper we demonstrate the system controlling a detailed simulation of the robot.Robots which are designed to operate in the real world must have the ability to deal with this environment. They must be able to operate in situations which their designers only vaguely envisaged and must have the ability to respond appropriately and quickly to unexpected events. Each of these subsystems is a complex program, and all have to work together perfectly for the robot to operate at all. Some of the subsystems are extremely complex, e.g., the tasks of perception.

In order to advance research efforts in the area of cooperative autonomy [9], a low cost autonomous surface craft, SCOUT (Surface Craft for Oceanographic and Undersea Testing) was developed by engineers at the MIT Department of Ocean Engineering. Design objectives include simplicity, robustness, versatility and improved operational utility. Four vehicles were fabricated during the summer of 2004 and a number of field experiments have been conducted using these craft. This paper discusses the design of the SCOUT vehicle and introduces some examples of the utility of this platform as a tool for improved software development, particularly in the area of cooperative autonomy. Describes an investigation into the adaptive control of autonomous mobile sensor platforms for providing oceanographic sampling. Mobile sensor platforms provide an ability to rapidly sample oceanographic data of interest for real-time input into ocean environmental models with the goal of reducing the modeling uncertainty by introducing selected sampled data.

It describes an investigation into the control of autonomous mobile sensor [10] platforms in a marine sensor network used to provide monitoring of transitory phenomenon over a wide area. A distributed network of small, inexpensive vehicles with heterogeneous sensors allows us to build a robust monitoring network capable of real-time response to rapidly changing sensor data. The major objective of this paper is to describe a framework for adaptive and cooperative control of the autonomous sensor platforms in such a network. This framework has two major components, a sensor that provides high-level state information to a behavior-based autonomous vehicle control system and a new approach to behavior-based control of autonomous vehicles using multiple objective functions that allow reactive control in complex environments with multiple constraints. Experimental results are presented for a 2-D target tracking application using a network of autonomous surface craft in which one platform with a simulated bearing sensor tracks a moving target and relays the target state information to a second vehicle that is moving in a classification mode.

## 3. Distributed Coordinated Mobile Sensor Control Target Tracking Scheme

The phases involved in the proposed scheme are:

- Multiple Sensor Tracking Environment
- Distributed Sensor-Target Assignment
- Coordinated Sensor Motion Control

#### 3.1 Multiple Sensor Tracking Environment

Multiple sensor platforms allow one platform to stay at the surface with a higher bandwidth link to other sensor platform. It operates under different topology to optimize their sensor-oriented tasks in the sensor. Network survivability is enhanced as the loss of one or even possibly several inexpensive sensors and absorbed with the redundancy inherent in such networks. Two networked sensors are in operation are fitted with passive, towed sensor arrays. Both sensors detect and cooperatively track an unknown target and begin in patrol mode in separate portions of operating area in order to optimize their sensor coverage.

Two sensor works together to track target objects by communicating target bearing and track estimate information between themselves. Sensors position respects with the target in a formation design to minimize uncertainty in target track estimation. While coordinated sensors have advantages that present challenges in their joint control to reach their combined potential. Inter-sensor communication is limited in bandwidth and carefully allocated in network. Any kind of central continuous control is likely infeasible and multi-sensor joint involved with sensing dynamic phenomena.

#### 3.2 Distributed Sensor-Target Assignment

In distributed sensor-target tracks a moving object from a set of discrete sensor observations. First it decides on the kinematic model used to describe object's motion. Constantvelocity model is chosen; it is simply to describe mathematically estimation motion of a constant velocity target. By using bearing sensor in target motion analyses. In passive ranging applications state parameters from target track are estimated using set of observations from a single moving sensor platform. With only one sensor, both temporal and spatial diversity are measured to estimate the target track. Parameters uses simultaneous measurements from two spatially distributed sensors from which an immediate solution of the target position. Successive position estimates will then be used to estimate target's velocity components.

Triangulating the position of an object uses passive angle measurements which is commonly present in the sensor. Consider the position estimation for a moving target from a moving sensor platform and analysis for 2D target position estimation and subsequent error analysis.

#### 3.3 Coordinated Sensor Motion Control

In Coordinated sensor motion control using multi-objective optimization in action selection that behaviors produce an objective function rather than a single preferred action. By both a scheme for representing functions of unlimited form and algorithm for finding globally optimal solution. All functions are piecewise linearly defined by the approximation of a behavior's true underlying utility function. Search is over weighted sum of individual functions uses branch and bound technique to search through combination space of pieces rather than the decision space of actions.

Only error introduced is in discrepancy between a behavior's true underlying utility function and piecewise approximation produced to the solver. Error is preferable compared with restricting function form of behavior output to linear or quadratic functions. Decision regarding function approximation accuracy is a local decision to the behavior designer has insight into what is sufficient solver guarantees to a globally optimal solution.

# 4. Experimental Results

In this section we evaluate performance of distributed coordinated mobile sensor control target(DCM-SCT) scheme for wireless sensor networking through ns2 simulation. One of the major contributions of this work is to control the multiple cooperating autonomous sensor platforms. To confirm the analytical results, we implemented distributed coordinated mobile sensor control target scheme in the sensor networking simulator ns-2 and evaluated the performance of techniques.

The performance of distributed coordinated mobile sensor control target scheme is evaluated by the following metrics.

- Propagation Noise
- Target location
- Time of arrival

Table 1: Propagation Noise			
No of nodes	Target tracking using TOA	DCM-SCT scheme	
5	5	3	
10	6.5	4	
15	9.5	7	
20	13	9	



Figure 2: Propagation Noise

Fig 2 demonstrates the Propagation Noise. X axis represents the number of node density whereas Y axis denotes Propagation Noise using both the existing Target tracking using TOA and proposed DCM-SCT scheme. When the number of node density increased, Propagation Noise gets decreases accordingly. The rate of Propagation Noise is illustrated using the existing Target tracking using TOA and proposed DCM-SCT Scheme. Fig 2 shows better performance of distributed coordinated mobile sensor control target scheme in terms of nodes density than the existing Target tracking using TOA.DCM-SCT Scheme achieves 15 to 25% less Propagation Noise variation when compared to existing system.

Table 2: Target Lo
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No of nodes	Target tracking	DCM-SCT	
	using TOA	scheme	
5	3	2	
10	6	3	
15	8	5	
20	12	7	



Fig3 demonstrates the Target Location. X axis represents the number of node density whereas Y axis denotes Target Location using both the existing Target tracking using TOA and proposed DCM-SCT scheme. When the number of node

density increased, Target Location gets decreases accordingly. The rate of Target Location is illustrated using the existing Target tracking using TOA and proposed DCM-SCT Scheme. Fig 3 shows better performance of distributed coordinated mobile sensor control target scheme in terms of nodes density than the existing Target tracking using TOA. DCM-SCT Scheme achieves 10 to 20% less Target Location variation when compared to existing system

Table 3: Time of Arrival	
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No of nodes	Target tracking using TOA	DCM-SCT scheme
5	0.18	0.10
10	0.23	0.15
15	0.28	0.20
20	0.35	0.28



Figure 4: Time of Arrival

Fig 4demonstrates the Time of Arrival. X axis represents the number of node density whereas Y axis denotes Time of Arrivalusing both the existing Target tracking using TOA and proposed DCM-SCT scheme. When the number of node density increased, Time of Arrivalgets decreases accordingly. The rate of Time of Arrivalis illustrated using the existing Target tracking using TOA and proposed DCM-SCT Scheme. Fig 4 shows better performance of distributed coordinated mobile sensor control target scheme in terms of nodes density than the existing Target tracking using TOA. DCM-SCT Scheme achieves 15 to 20% less Target Location variation when compared to existing system.

## 5. Conclusion

We discuss the problem of tracking targets in multiple autonomous sensor platforms which is leads in many confusion and has poor coordination in distributed environment. It requires high computational complexity and communication energy. So we performed a distributed coordinated mobile sensor control target tracking scheme. It provides a sensor which has high-level state information about the process. Propagation noise is reducing the system that helps to give fast transmission in the network. Time of Arrival (TOA) information provides a connection between target location and mobile sensor location.

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