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Model for autonomous agents in machine-to-machine navigation networks

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Summary

Machine-to-machine (M2M) is an evolving architecture and tends to provide enormous services through the swarm presence of the networked devices. Localization is one of those services. Previous localization techniques require complex computation that is not suitable and affordable in such architecture. Moreover, integrating intelligent multiagents on these ubiquitous devices makes the network more independent and reactive requiring for a less complex localization model. This paper reviews the present localization techniques and discusses their infeasibility for M2M communication while proposing a mathematical model that is derived from Anderson model for the distributed structure of machine-type-communication network involving autonomous agents. This paper has made an attempt to use the property of Anderson model that structures the distributed objects. This paper also classifies autonomous agents according to their functionalities in a navigational network. Recently, Anderson model have been customized for implication of optical communication; in this paper, the proposed mathematical model involves intelligent agents for localization that aim to reduce complexity of positioning computations for nodes having restricted computational resources and battery life, which are the main characteristics of M2M communication.

KEYWORDS

machine-to-machine, multiagents, positioning

1 | INTRODUCTION

Machine-to-machine (M2M) communication paradigm is an evolving infrastructure grasping every aspect of life while acting autonomous and react intelligently is a fundamental characteristic of involved applications. Autonomous communication usage is already tested and implemented in unmanned vehicles network environment.[1] By integrating intelligent and autonomous agents, the unmanned cars, aircrafts, and spacecrafts can perform many functionalities while communicating and supporting each other through machine-type-communication (MTC) standard protocols. Navigation[2] is one of those essential functions that is required by every other device either stationary or been mobile. Numerous applications involve tracking and localization capabilities for military, commercial, and public safety. As technology upgrades and smart communication ecosystem[3] emerges, machines can intelligently navigate and localize other machines without any human intervention, although the main characteristics[4] of an M2M ecosystem is different and restricted from the rest of the wireless communication paradigm. The nodes involving are restricted for battery usage and perform limited computations. These nodes send and receive small amount of data and work through the processing in the form of group, since their network life depends on usually small battery and cannot afford high computations. The main objectives of these nodes are to observe the environment and collect data, making them a good source for navigation without involving complex processing.[5] For controlling these nodes, multiagent system (MAS) is integrated into the nodes. These autonomous agents make the network a self-organizing and adaptable architecture. [6]

Recent research by NASA[7] has enabled a spacecraft to work cooperatively based on M2M communication for navigating other spacecrafts, through autonomous agents using inertial sensor measurements, cooperatively working out their positions. Usually, the autonomous agent is a software agent; all the measurements and constraints calculations are performed onboard, and no hardware upgrades are required. Using different frameworks of navigation, agents jointly infer their locations both in temporal and spatial domains.[8-10] But this navigational network is up till now restricted to space domain. Every autonomous agent deployed in a such infrastructure is an asset to every other autonomous agent enhancing and supplementing traditional state methods. Due to their cooperation, communication load can be reduced on ground navigation systems and also reducing reliability on global positioning system (GPS) weak signals. Updates in navigation are transfered through cross-communication between agents in the navigational network coupled with onboard estimates for correct positioning.

Because of the increase in dependence on satellites architecture and ground-based navigation system, navigation has become a complex issue at a larger scale. It has many present issues, such as jamming; it can be easily jammed as the transmitted signals are so weak,[11] and the frequency used by the system is very common, ranging from 1227.60 to 1575.42 MHz. Some disruptions are natural, those include noise induced due to solar flares and high intensity of ionosphere disturbances. Other disruptions are man made such as transmission of unwanted radio frequencies, interference from other TV transmissions, and microwave links. The efficiency also degrades in dense urban environment as building blocks attenuate and reflect the signals, thus providing a bad quality of reception. Besides GPS, no technology is ever close to providing complete coverage with accuracy. Commercial companies such as Polaris[12] and Skyhook[13] provide expensive subscription to users, but still not efficient for providing better navigation. As technology has evolved it has enabled the mobile devices to receive directions from Global System for Mobile Communications (GSM) and wireless local area network (WLAN). These alternate methods are limited to a certain extent, as they only generate single positioning. The technology should be upgraded and provide an alternate efficient path for the user, vehicle, and aircraft.

Previously, Earth-based assets[14] were responsible for providing navigation parameters such as computation of ranging signals,[15,16] using inertial measurements and through observation of orbital determinations. All of these methods require high computations that are not suitable for M2M communication architecture, as usually a typical node in such architecture comprises of 1Gb of memory and a standby time using 2.5 Ah battery. The existing localization techniques also lacks a less complex mathematical model for integrating MTC type nodes and where each node can consist of autonomous multiagents. The MAS technologies such as multiagent oriented programming (MAOP) integrates different governance properties in such a network while controlling the devices exogenously or endogenously. In this paper, current navigation network is reviewed with respect to mathematical computations required by autonomous machines communication network. Moreover, a computationally efficient mathematical model for autonomous localization is also proposed in this paper that is based on Anderson model.[17] The Anderson model is named after physicist P.W. Anderson who introduced a model for disordered objects and senses through their spectral energies. Up till now the Anderson model has been used and customized for a number of different problems including optical fiber communication. Through this proposed model, localization computations are simplified and efficiently resolve positioning communication. This paper also classifies the multiagents used in localization scenario.

The structure of this paper is as follows. Section 2 discusses the related work with regard to autonomous navigation. Section 3 discusses M2M network and review existing localization techniques and their infeasibilities for the nodes involved in that network. In Section 4, autonomous agents are classified according to their roles for estimating positioning scenarios and presented the proposed mathematical model for autonomous agents for localization based on Anderson model.[17] For effective implications of the proposed model, use case study is performed in Section 5. The paper concludes the research through the conclusion and future research in Section 7.

2 | RELATED WORK

Most of the previous work are based on cooperation techniques by nonautonomous devices (vehicles) for determining locations. One article[18] uses the audibility information generated from devices; first phase of the algorithm sets time offset maximum likelihood estimation (MLE) and second phase imply differential source location algorithm on MLE.

In Bejuri et al,[19] the focus is based on ubiquitous mobile navigation systems. It has proposed techniques for intelligent ubiquitous locating positions, but only limited to the mobile phones. The paper[20] discusses cooperative navigating possibilities in vehicular-to-vehicular networks. The authors have constructed a mathematical model and simulated cooperative positioning techniques for vehicular ad hoc networks (VANETs) architecture. The literature also have proposed an algorithm for identifying clusters of cooperative vehicles. The following paper[21] has expressed the issues with Global Navigation Satellite System (GNSS) and the loop holes that are present in the system. It discusses the scenarios of peer-to-peer navigation when there is a failure detected from a GPS system. It also presents benefits of cooperative peer-to-peer positioning system. A comparison is performed between a typical GNSS system, a centralized navigation approach verses a peer-to-peer positioning system. It explains the architecture of cooperative positioning from a technical view and the challenges it faces for future developments. The article[22] surveys the cooperative positioning with respect to vehicular networks and terms as intelligent transportation system (ITS). It discusses the applications and the constraints encountered by a successful vehicular cooperative navigation system. It presents the current trends of cooperative positioning research in terms of VANET infrastructure.

Moreover, the article[23] discusses M2M communication popularity and its implications in vehicular networks and explains the factor that can improve networking in VANET. The vehicles communicate autonomously and supporting several smart applications while the paper also discusses the network paradigm modules that enhances the vehicular inter working. Further challenges are discussed that are faced by the effective deployment of smart applications in vehicular networking environment. The article[24,25] proposes a localization technique for indoor and outdoor Internet of Things (IoT) services. The technique is divided into two phases. The first phase splits the region into small grids and in the second phase that is the refinement phase. Received signal strength indicator (RSSI) values of nodes are used in refinement phase, such that RSSI values are large if the distance is shorter and vice versa. Blind nodes are encapsulated in grid formation. By applying Pythagoras theorem, position coordinates are estimated. Mobile agents termed as "seekers" are targeted devices in the paper.[26] The technique uses a nongradient-based approach known as "particle swarm optimization" (PSO) for decaying profile in real-time system. Two different variations of PSO are simulated (1) having inertia weights and (2) constriction of PSO. The paper[27] proposes a cooperative localization technique for mobile agents. The communication between device agents are either through multihop or single broadcast fashion. Every agent is required to rebroadcast the received messages so every member of the group receives the coordinates. Proprioceptive sensor of each device agent measures the self motion. An extended Kalman filter (EKF) is applied to the motion equation for estimating coordinates.

The algorithms proposed in the above articles are very extensive and require complex computations; moreover, none of them used multiagents techniques for localization. The M2M devices are small in size and have limited computational resources, and the processing is bounded to less energy consumption. This paper proposes a less complex mathematical model based on the Anderson model[17] for smart devices involving intelligent agents for sensing the spectrum characteristics and computing the coordinates.

3 | M2M COMMUNICATION FOR NAVIGATION

Multiple devices and autonomous machines including sensors, actuators, unmanned vehicles, and aircrafts interact and take decisions, providing value added services all existing in an ecosystem of M2M. It is a network of intelligent machines and smart devices.[3] The city that implements such infrastructure is called Smart City. Barcelona[28] is an example of such cities.

As discussed above in Section 1, GPS navigation has many issues but those issues can be reduced by effective implication of the M2M navigation network.[29] The devices(machines) cooperatively share location information and estimating their positions and directions. Machines have the knowledge base (databases) integrated to make them intelligent and autonomous for the reason they have ability to compute location estimates onboard and getting any updates from the GPS system. This information is analyzed before following them. The infrastructure works very effectively by collaborating and cooperating with each involved device for accomplishing tasks. Each machine or device in this ecosystem is governed by an intelligent and autonomous agent, which is discussed in detail in Section 4. Proper working of these agents enables the following characteristics in the infrastructure such as (1) adaptability, (2) self-healing, (3) self-organizing, (4) scalable, and (5) autonomous.

The M2M communication infrastructure is capable of handling interpretation between agents. The network deploys compressed protocols[4] for generalizing communication structure for communicating and detecting every other machine.

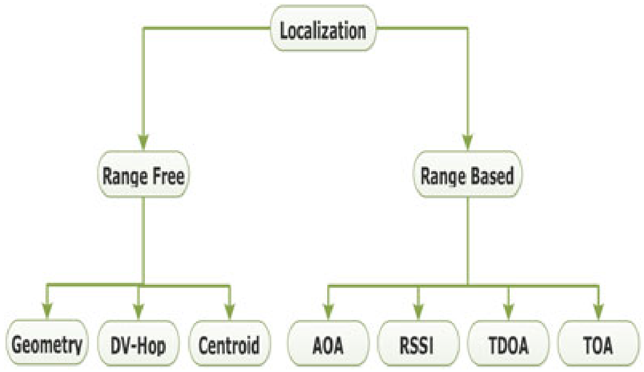

FIGURE 1 Classification of localization techniques. AOA, angle of arrival; RSST, received signal strength indicator; TDOA, time difference of arrival; TOA, time of arrival

TABLE 1 Machine-to-machine (M2M) localization techniques specifications

Method	Technologies	Accuracy	Type	Infrastructure
Centroid	Wi-Fi, BLE	60%	Range-free	Fixed
DV-Hop	Zigbee	60%	Range-free	Ad hoc
MCL	Wi-Fi	50 %	Range-free	RFID tags
TOA	Wi-Fi	5 meters	Range-based	WLAN
TDOA	Wi-Fi, UWB	13 cm	Range-based	WLAN
RSSI	WiMax	6-7 meters	Range-based	Fixed, cellular

3.1 | Localization techniques in M2M

Localization techniques can be classified as range-free and range-based categories as shown in Figure 1 of interconnected nodes. Table 1 lists the specifications of localization techniques that can be applied to M2M network. The article[30] classifies the range-free localization techniques into two types, which are as follows: (1) incremental and (2) concurrent depending on the computing and the assignment of coordinates of nodes. Range-free localization protocols are discussed below.

- **Centroid:** Location estimation through centroid technique is based on the concept that target device position is calculated by the known points of the anchor nodes existing in the transmission range.[31] The precision level of centroid technique is low and used in dense network. It must contain fixed nodes those position are known. Through the known positions, unknown positions are calculated as follows:

$$\bar{y} = \frac{\sum_{i-1}^{N} w_i y_i}{\sum_{i=1}^{N} w_i}. \tag{1}$$

  Here, w_i represents weight of the ith fixed node, N is anchor number, and y_i is the current position. w_i can be calculated as follows:

$$w_i(t) = \frac{m^i_{rec}(t)}{m^i_{sent}(t)} \tag{2}$$

  Here m_{rec} and m_{sent} are the received and sent messages in time t. Only 90% weight is considered for accepted messages.
- **DV-Hop:** Uses anchor nodes (an M2M device behaving like a relay node) in a range-free algorithm broadcasts packets to the neighboring device providing them information about the localization and helping to navigate.[32] A flag is set in the packet information indicating the hops count that is achieved before reaching the current receiving device. When a packet is transmitted from one device to another the hop count, which is the flag is incremented. In start, it is initiated to one. By knowing the value of flag, an assessment can be made about how far is the receiving device. Average distance per hop (ADH) is maintained and broadcast along the packet; by using ADH value, each device can calculate their distance from the neighboring devices by multiplying their hop count with ADH. This algorithm

has problems with accuracy in sparse environment. DV-Hop is best in an urban environment where the number of devices are many, although many improvements are made in this algorithm for the sparse M2M network.

- **Monte Carlo localization (MCL):** It is also known as "particle filter localization."[33] This algorithm is mostly used for localizing robots, but it is also used in the M2M network. The algorithm implies the term "particle filter" for estimating their location. Where each particle is the state of any particular location. Through artificial intelligence the device predicts the state by filtering through present particles. Recursive Bayesian estimation is used for resampling the particles. For observing the state, the device involves sensors according to which guesses are made, which are transformed into particles. Finally, after processing all these particles, they are converged to an accurate location.

Range-free positioning techniques[34-39] are based on the characteristics of RF signals used in communication. Range-based approaches[40-44] use complex mathematical computations to calculate angles and distances between two nodes those are transmitting and receiving signals while maintaining communication between them. Following range-based techniques are discussed below.

- **Received signal strength indication (RSSI):** Localization information is estimated by measuring the received signal strength. Scales are maintained by comparing the signal strength with distance traveled. Propagation loss of the signal strength provides estimated distance using following Equation 3.

$$p_r(d) = \frac{p_t G_r G_t \lambda 2}{(4\lambda)^2 d^2}. \tag{3}$$

  Here, λ is the wavelength of the signal, p is the power of the signal, and G is the gain of the antenna.
  Time of arrival (TOA): In this technique, time of receiving signal is measured along with the wavelength of the signal. The difference between measured values by a relay or anchor devices and unlocalized device provides estimation of the location. This technique is very precise, but it is expensive and due to which it is unsuitable for common M2M network, which consists of cheap devices operating on very low energy.
- **Time difference of arrival (TDOA):** For using this technique, the device usually is equipped with speaker and microphone. The time difference between the arrival of the signal and ultra sound estimates the location of the transmitting device. The variable involved in this computation are t_{delay}, that is, the wait time of the relay or anchor device after which it generates "Chirps" for ultra sound signal, t_{radio} is the received time of data signals at the unlocalized device, and t_{sound} is the received time of "Chrips" ultra sound signal. Location is estimated by differencing the above variable through the following Equation 4.

$$d = (s_{radio} - s_{sound}) * (t_{sound} - t_{radio} - t_{delay}). \tag{4}$$

- **Angle of arrival (AOA):**Devices can be localized by estimating the angle of receiving signal between two relay or anchor devices. Triangulation techniques[45] are applied for estimating the location through using the angles of the signals.

4 | AUTONOMOUS AGENTS IN M2M

Agents are intelligent entities or software programs that perform their tasks without any human intervention. They have 3 basic components through which they are operational (1) inference rules, (2) knowledge base database, and (3) actions repository. They are goal-oriented and social as well. They observe and perceptions are translated to take initial steps, compare and plan their actions after processing through their inference rules. Autonomous agents are constructed to be independent, respond back without any human support on their own decisions by working through their knowledge base. They are also capable of updating their knowledge, migrating, and collaborating with other multiagents. Their priorities are set for best action plan for achieving their objectives. An autonomous agent architecture is shown in Figure 2 consisting of main module for M2M based navigation. Integrating an autonomous agent in a machine or device creates intelligent and automated interconnected machines ecosystem based on 3 components:

1. Embedded processing;
2. Controlling and managing applications; and
3. Communicating and sharing data.

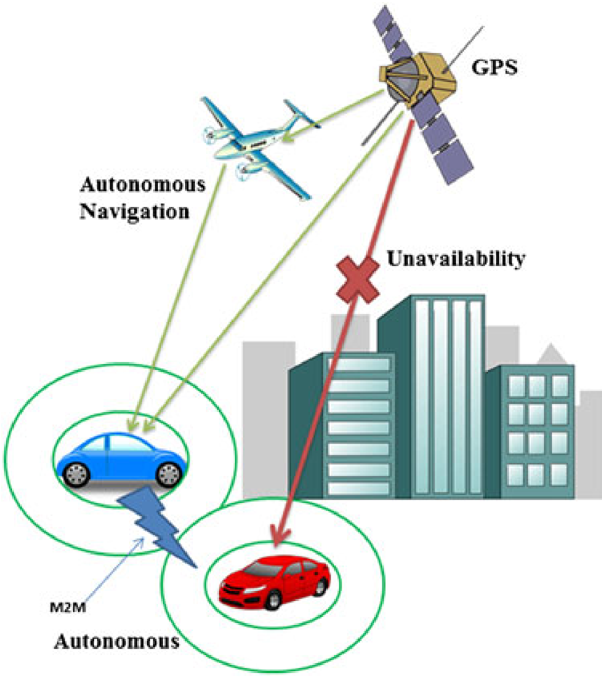

FIGURE 2 Machine-to-machine (M2M) navigation network

4.1 | Autonomous agents vs normal daemons

A program executes continuously and handles periodic tasks requests that are received by the computer systems. Such programs are termed as daemon. Related requests are forwarded to other programs or processes by the daemon programs. Such as there is an HTTPD (hypertext transfer protocol daemon) related to each server of pages existing on the Web. This daemon continuously waits for request coming from users on the Web. In case of localization, the software daemon receives the data coming from localization devices and passes the data. The parsed data are converted into messages. The combination of messages provides the estimation of speed, position, and altitude ranging between different precisions.

Whereas in artificial intelligence an intelligent agent observes data from sensors and act autonomously through actuators, it has the ability of analyzing the data before acting in an environment. In case of localization, the agent interprets the data as map and performs learning and reasoning upon it for estimating the location in an unknown environment.

4.2 | Interfacing autonomous agents

In each electronic device autonomous agent is integrated through software or using Agent Communication Language (ACL). There are a number of frameworks available for interfacing autonomous agents with the electronic device or machine, Table 2 lists their specifications. One of those frameworks is FIPS (Foundation of Intelligent Physical Agents)[46] created ACL framework. In case of navigating, a developer will create an agent that is aware of the location and positioning algorithms. The goal of this agent is to estimate directions, positions, and cooperate with other autonomous agents,

TABLE 2 Multiagent system (MAS) frameworks For machine-to-machine (M2M) localization

Framework	Function	License	Distributed	Programming language
ABLE	Building intelligent network	Open source	Yes	ARL
SimAgent	Agent Development Kit	Open source	Yes	Lisp
Boris	MAS Development Platform	Open source	Yes	Lisp, C#, Java
Behaviour Composer	Agent-based computer models	new BSD	Yes	NetLogo
Jack	Agent Development Platform	Proprietary	No	Java
TerraME	Network Agent Development Platform	GPL	No	C++
Fluxy	Multiagent Platform	Academic licence	No	Python

integrated into other devices and machines for correct positioning while sensing their surroundings. Following are the benefits provided by autonomous agents:

1. Applications are universal and independent from the devices on which they are running;
2. Connecting and interacting with devices are dynamic; and
3. No human interaction is required; best possible actions are performed.

4.3 | Agents classification

Agents can be classified into many different types according to the tasks that they perform. This paper classifies the agent types involved in navigation into two categories: (1) computative agents and (2) decisive agents.

1. **Computative agents:** Computation logic provides a rigorous and well-defined framework for developing procedures and semantics for multiple tasks performed by individual agents while defining interaction formats for agents existing in multiagents systems. The computational cost is a major factor in M2M architecture; the agents in this network should work at lower computational cost. Computational agents are usually encapsulated objects, recognizing computational algorithms such as energy controller, distance calculator, or spectrum identifier. This type of agents observes the measurements and compute results, but they have restricted deliberation capabilities. The types of agents related to this category are reactive agents, energy agents, communication agents, sensing agents, etc. Their functionalities relate to the observations that they experience. Agents have finite but significant computational resources. Explicitly, agents show beliefs according to their computational resources. These beliefs cater the agent's environment in which they reside. Each cognitive action related to agent behavior uses their own computational resources. These agents can be controlled by decisive agents. Their intelligence is constrained to the measurements only and does not involve taking actions. Extensive computational resources are used by these agents. Analytical solutions and experimenting the problems are also under their responsibilities. There are two fields upon which they can act: (1) hardware and (2) software. In hardware, these agents are embedded along with sensors and actuators for measurements and observations.
2. **Decisive agents:** These kinds of agents act as coordinators of the system. Collaborate, deliberate reasoning, planning, and taking actions are the main functions of this category of agents. Decisive actions should be faster and reliable. Through the usage of command agility, decision dominance can be achieved. Each action is a resultant output of a certain condition. They take results from computative agents, compare from their knowledge bases, and plan their actions. The pairing of condition/action forms a rule. A condition can be a certain sensitive condition or formula. The rule is basically of two types: (1) message action rule and (2) cognitive action rule. Formulating the rules creates a knowledge base through which all of the reasoning and planning are based and provides a stability while governing the system. These rules relating to some coordinates can be shared with other devices in the machines based navigation network. Controlling of the agents is an extremely complex issue. Planning agents, reasoning agents, and control agents are the types of agents involved in this category. These agents cater complex views, those that are necessary for making correct decisions. Coordinating and decision making is a challenging task in the large multiagents system. The system may be comprised of as many agents as in case of M2M communication network, where these agents are spatially distributed. Decisive agents control these heterogeneous agents, circulate decision in whole group, and collect information. Not a proper coordination can become a bottleneck in the communication process. Previously, a decentralized decision agents has successfully elaborated the communication and while creating an information asymmetry. Many benefits can be achieved by agents working in background, retrieving information and deciding decisions collaboratively.

4.4 | Calculative measurement

For estimating positions and directions, the agents have to calculate following measurements. The measurements that an agent communicate may include the following:

- The distance between the communicating agents, such as in IEEE Wi-Fi Standard 802.11 certain protocols are defined for calculating distance between two peer nodes of Wi-Fi;
- Relative position of two autonomous and cooperating agents;
- Altitude differences of two communicating and navigating agents; and
- Some autonomous agents clocks might not be synchronized; the differences in their clocks should be calculated.

4.5 | Mathematical model

A mathematical model can be computed for M2M localization integrated with intelligent multiagents. This paper has proposed the model that is based on the Anderson Model.[17] The Anderson model is structured on Hamiltonian principle. The Anderson model uses techniques for spreading and localizing the electrons and recently applied to image processing in optical fiber.[47] The same technique with customization can be deployed for detecting and navigating the smart devices through their spectrum energies. The multiagents that are governing the devices senses spectrum energies of the devices and by using the measurements discussed in the previous section calculates the distances. Let $h = (h_n)$ be a set of independent machines (devices) distributed in an area indexed by $n\epsilon Z$. The probability that the devices can be found lies on the Borel probability. Borel sets $B \subset R$. Then the overall probability can be structured as in Equation 5

$$P(h_{n_1}\epsilon B_1 \ldots \ldots h_{n_L}\epsilon B_L) = \prod_{j=1}^{L} P(h_{n_j}\epsilon B_j). \tag{5}$$

Each device has one agent or multiagents "A" as Equation 6.

$$h_0(A_i, \ldots. \ldots A_n). \tag{6}$$

Every device has a potential V_n to be detected by the multiagents of other devices. Hence, the total potential of a certain device can be calculated as Equation 6

$$h_n = h_0 + V_n. \tag{7}$$

The random potential is the RF measurement values that each device exerts. The intelligent agents sense this potential and weigh the decisions of location estimation. Through the implication of spectral theorem, the definitions of surroundings can be estimated. The possible energies of the devices can be given by the spectrum $\delta(h_n)$. A spectrum can be created deterministically from those energies summation. If there are no large gaps present between, then the spectrum has the vital intensity that can be computed as Equation 8.

$$\delta(h_n) = \sum. \tag{8}$$

The multiagents measure the behavior of the spectrum and computes the probabilities. This spectrum is a combination of 3 types of spectrum subspaces computable by Equation 9

$$\sum = S_p \oplus S_{ac} \oplus S_{sc}, \tag{9}$$

S_p = subspace of point spectrum
S_{ac} = subspace of absolute continuous spectrum
S_{sc} = subspace of singular continuous spectrum.

Observing the physical institutions of these subspaces provides multiagents with information on the characteristics of the regions surrounding the scattered devices. The electromagnetic spectrum is the input to the agent autonomous system, and through their knowledge base, the agent provides location estimation, such as S_p belongs from a compact region and is bound state, whereas the nature of S_{ac} is a scattered states region. By using the dynamical properties of Hamiltonian structure, the algorithm can be made more reactive and dynamic.

4.6 | Agents measurements

Depending on the above measurements, the following model can be derived for cooperative navigation. Let "N" be the set of all present autonomous agents integrated in vehicles or aircraft/spacecraft. "M" is the set of all M2M devices, "U" is the set of anchors, and there might be possibility of receiving signals through satellite; therefore, "G" is the set of satellites. M_n, G_n, and U_n are the set of devices, satellites, and anchors autonomous agents, respectively. The information attained from satellite is "I_{gn}", the positional information attained from terrestrial anchors denoted by "T_{un}", and the information received from an autonomous agent of the neighboring M2M device is denoted by "A_{mn}". Also, $g\epsilon G$, $u\epsilon U$, $m\epsilon M$, and $n\epsilon N$. The total information obtained by a certain agent is calculated in Equation 10:

$$N_n = I_{gn} \cup T_{un} \cup A_{mn}. \tag{10}$$

The unknown, which are left are $W = [P_m C_m]$, where $P_m = [x_m y_m z_m]$, $P_u = [x_u y_u z_u]$, and $P_g = [x_g y_g z_g]$ are the sets of positional values of certain autonomous agent, of a terrestrial anchor, and of a satellite, respectively. The distance between the terrestrial anchor agent and the M2M device agent can be calculated as Equation 11:

$$D_{um} = ||P_u - P_m|| + Noise_{um}. \tag{11}$$

Here, $Noise_{um}$ is the noise present in the communicating spectrum band. The symbol "||.||" represents Euclidean distance. The distance between the satellite and the autonomous agents is calculated through Equation 12:

$$D_{gm} = ||P_g - P_m|| + C_m + Noise_{gm}. \tag{12}$$

Here, C_m is the clock bias of the agent. The measurement model can be created through following calculations:

1. The distance between an autonomous agent "i" and the neighboring agent "j" can be calculated as Equation 13 having $Noise_{ij}$ is the noise present in the communication channel.

$$d_{ij} = ||x_i - x_j|| + Noise_{ij}. \tag{13}$$

2. The relative position between the autonomous agent "x_i" and neighboring agent "x_j" can be calculated as Equation 14:

$$r_{ji} = x_j - x_i. \tag{14}$$

3. If the clock of an autonomous agent "c_i" is not synchronized with neighboring agent "c_j" clock, the difference is calculated as Equation 15:

$$\Delta C_{ji} = c_j - c_i. \tag{15}$$

4. For calculating the difference in altitude in case if an aircraft is communicating and sharing autonomous navigation with a ground vehicle. In case of ground vehicle-to-ground vehicle, the values become $z_j = z_i$. The altitude difference of an agent "z_i" and the neighboring agent "z_j" can be calculated as Equation 16:

$$\Delta L_{ji} = z_j - z_i. \tag{16}$$

Through the computations of these variables, the agent enables the device to be located and navigated. The main emphasis of the mathematical model is to reduce the complexity of computational components involved in localization as M2M communication network devices are energy constrained and have little processing resources.

5 | USE CASE STUDY

The cost of computation for positioning the devices can be effectively reduced, as the complexity of the proposed model is only $O(n)$. To study deeply the effects and for the implication of the proposed model, certain use cases are discussed below. Table 3 lists main functions related to the type of intelligent agents and instruments that can be used in this localization model.

TABLE 3 Processing navigation and related multiagents

Function	Agent Type	Role	Instrument
Synchronize	Control agent	Send and receive beacon to synchronize up	Proximity sensor
Detect radio frequency	Communication agent	Sense the surrounding radio frequencies from neighboring devices	Radio direction finder
Spectrum sensing	Energy agent	Sense the energy spectrum reflected or emitted by the devices or objects	Doppler radar sensor
Position estimation	Reactive agent	Correct and estimate self position	Altimeter
Environment sensing	Reasoning agent	Detect the surroundings and compare with knowledge base for correct navigation	Vision sensors
Movement	Planning agent	Take decisive action for correct navigation	Actuators

5.1 | Terrain sensing

There are many requirements for accurate terrain sensing, especially for navigating devices such as, many of the times GPS navigation has lead the vehicles teetering on a cliff edge and fall from it, localizing the autonomous robots within a building and providing them information of the surrounding environment and maneuvering a car in densely populated urban terrain, etc, are some of the examples that require estimation of the terrain before mobility.

By the implication of Equation 9 of the proposed model, the device can become capable of sensing the terrain. Choosing the appropriate agent, such as energy agent from Table 3, the energy agent of the device analysis the spectrum signatures and generate an estimation of the terrain. The estimations can be of various types, depending on the knowledge base of the energy agents such as the nature of the terrain consists of scattered objects/devices, belongs from a compact region, and is bounded environment or wide spaces, etc. The analysis can alert the entity such as an autonomous vehicle or robot or user of possible wrong turn or maneuver. Such instructions are at a less cost as compared to vision sensors, which not only cost more but also require an extensive knowledge base for identifying the objects or devices.

5.2 | Positioning

Previous positioning algorithms are more complex and require high computational cost, which is a negative aspect in case of M2M network. By using the information sharing capability of the subjective network, Equations 11 to 16 of the proposed model can enable the device to estimate the residing location and calculate certain distance or a trajectory. By using the knowledge base of communication agent from Table 3 of a device, analysis can be made for the shortest path availability. Since IoT is based on the M2M network, many of the applications,[48-49] such as smart transportation, autonomous moving of robots, and smart postal service, require accurate positioning in less time. The proposed model can effectively work in diverse situations even if the system stop receiving navigational information from Wi-Fi hot spots. Each bus or drone working in a group share their communication agent knowledge base and together work out their positions data points in less cost and efficiently while forming an autonomous network in which collaborating and coordinating with each other.

6 | IMPLEMENTATION

The possible implementation and simulation methodology can be achieved through using of two systems. One system is responsible of computational activities of wireless signal received from other vehicles and sensors. After evaluation of data, decision making is transferred to the second system that handles the intelligent agents. The actions are performed through that module (model shown in Figure 3). With simulation perceptive first module can be implementable through Mason framework[50] and Jade software can be used for simulating autonomous agents. The deployment area is considered as 100 m × 100 m with 50 sensor nodes. Number of iterations were 40. During simulation, Gaussian noise was incorporated. One of the result obtained is shown in Figure 4. The result obtained from simulation achieved better localization in less time. The results achieved are 40% more precise even after increasing the distance till adoptable range as shown in Figure 5. Moreover, due to less complexity of the algorithm, it can be easily managed by M2M communication system.

6.1 | Pros and cons

This mathematical model has great potentials for M2M communication architecture, and by expanding the Hamiltonian parameters, the localization errors present in larger gaps can be covered. There still exist many challenges for precise navigation that needed to be addressed such as positioning while in variable speed, cell phone dead zone coverage,

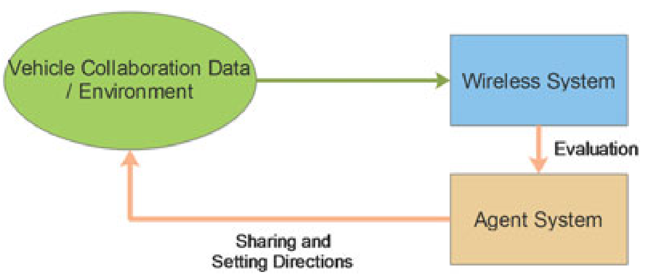

FIGURE 3 Implementation model

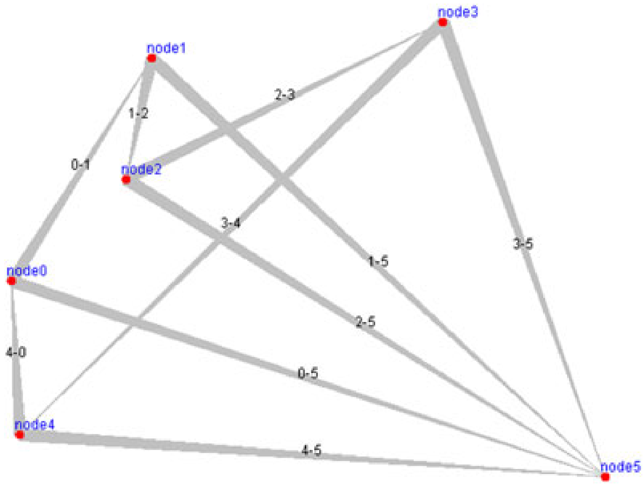

FIGURE 4 Simulation scenario with 6 nodes

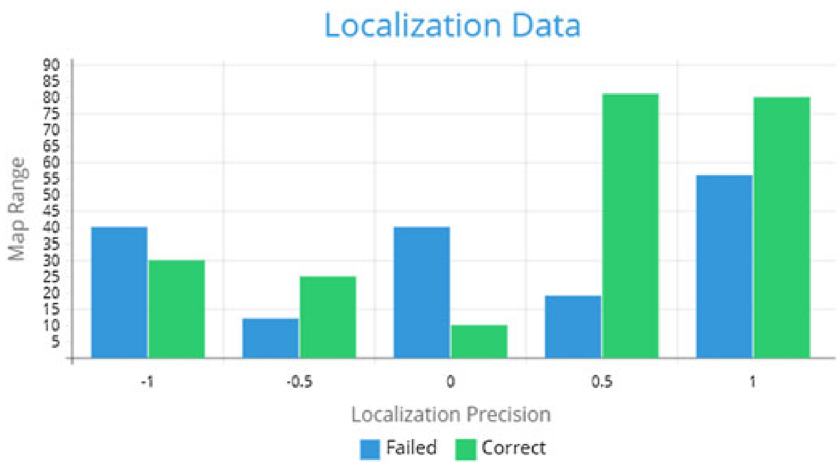

FIGURE 5 Localized record

and localization in sparse presence of devices. These and other issues should be carefully and critically considered for future research.

7 | CONCLUSION

In this article, a review was presented about localization techniques for M2M communication networks. The techniques comparison was discussed regarding multiagents scenario and their infeasibilities for the machines-based communication network. Intelligent agents were explored and classified in regard to navigation for MTC. By adopting the Anderson model for autonomous M2M localization purpose, a mathematical model was proposed. The proposed scenario tends to reduce the complexities of localization computations and structures the technical specifications of multiagents operations in Table 3. Related use cases are studied for effective implication of the proposed model.

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