Autonomous Navigation and Teleoperation in Robots using Machine Learning

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ABSTRACT
Human-robot interaction most challenging task such as control, monitoring and navigation. We explore the unique challenges posed by the remote operation of robots. Teleoperation widely make use of short messaging service, this method not efficient for robotic control, monitoring and navigation. Rapid development in robotic technology effective monitoring, control and automated navigation are need, this paper we developed a system for the remote operation in robots is based on GPRS for monitoring and control. Robot act as artificial intelligent agent to avoid obstacle by using artificial intelligence approach namely machine learning algorithm called decision tree learning for automated navigation during absence of remote operator.

Keywords
Human- robot interaction, GPRS, autonomous navigation, machine learning, decision tree learning, teleoperation.

1. INTRODUCTION
AS quick growth is being made on all frontiers of robotics technology, many of the key mechanism necessary for developing socially situated autonomous robot systems are falling into place. The social robots are place in museum, shopping mall, and in many other places for the purpose of monitoring and research. These robots are control and monitoring places manually by a operator. The distance between the operator and the robot is limited.

These robots are semi- autonomous it can operate based on user command with the absence of the operator it cannot automate for monitoring. Operator control robot via Network cable, Bluetooth, Zigbee and so on. Remote monitoring and control is impossible in those robots.

In the paper we proposed a system that takes an advantage of remote monitoring and controlling the robot using the GPRS the user can remotely controlling and monitoring the robot. With the absence of the user the robot can automatically monitoring the environment and react accordingly. In automated monitoring obstacle is main problem to avoid obstacle during monitoring machine learning and decision making algorithm used as a artificial intelligent technique. Through this methods the robot can monitor the entire area without any disturbance.

For monitoring , webcam is interfaced in robot it can streaming the video in mobile as it monitored and stored a copy of steaming video in the server during the absence of user.

2. RELATED WORK

2.1 General Packet Radio Service
General packet radio service (GPRS) is a packet oriented mobile data service on the 2G and 3G cellular communication system's global system for mobile communications (GSM). GPRS was originally standardized by European Telecommunications Standards Institute (ETSI). In 2G systems, GPRS provides data rates of 56–114 Kbit/second. The GPRS core network allows 2G, 3G and WCDMA mobile networks to transmit IP packets to external networks such as the Internet. The GPRS system is an integrated part of the GSM network switching subsystem.

- The GPRS offered several services such as SMS, MMS, PoC, P2P, and P2M and so on.
- The GPRS supports several protocols such as IP, PPP and so on.

GPRS will store and forward the IP packets to the phone even during handover

2.2 Machine Learning
Machine learning is a core subarea of artificial intelligence. It is very unlikely that we will be able to build any kind of intelligent system capable of any of the facilities that we associate with intelligence, such as language or vision, without using learning to get there. These tasks are otherwise simply too difficult to solve. Further, we would not consider a system to be truly intelligent if it were incapable of learning since learning is at the core of intelligence.[13]

Machine learning algorithms can be organized into a taxonomy based on the desired outcome of the algorithm or the type of input available during training the machine.

- **Supervised learning** generates a function that maps inputs to desired outputs
- **Unsupervised learning** models a set of inputs.
- **Semi-supervised learning** combines both labeled and unlabeled examples to generate an appropriate function or classifier.
- **Reinforcement learning** learns how to act given an observation of the world.
- **Learning to learn** learns its own inductive bias based on previous experience.

Examples of machine learning are optical character recognition, face detection, spam filtering and so on.

2.3 Decision tree learning

Decision tree learning is used in machine learning[13]. The goal is to create a model that predicts the value of a target variable based on several input variables. Decision tree is a flow chart like structure, where each internal (non-leaf) node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf (or terminal) node holds a class label. The topmost node in tree is the root node.

2.4 Navigation

A navigation system can usually be divided into two parts: a global planner and a reactive collision avoidance module. The global path planner generates minimum-cost paths to the goal(s) using a map. As a result, it provides intermediate goals to the collision avoidance routine that controls the velocity and the exact direction of motion of the robot.

2.4.1 Planning

The idea of path planning is to let the robot always move on a minimum-cost path to the nearest goal. The global planner, in contrast with the collision avoidance routine, does not suffer from a local minimum problem, since it plans globally. With grid-based maps the minimum-cost path can be computed with algorithms like dynamic programming or A*. Topological planning is more efficient because of the compactness of topological maps. Topological planning is between three and four orders of magnitude more efficient than planning with grid-based maps. This is despite the fact that plans generated with topological maps are typically between one and four percent longer than plans generated using grid-based maps. A planner alone, however, is not sufficient to control the robot, because it does not take robot dynamics into account and because learned maps are incapable of capturing moving obstacles.

2.4.2 Collision avoidance

The task of the collision avoidance routine (also called obstacle avoidance) is to navigate the robot to sub goals generated by the planner while avoiding collisions with obstacles. It adjusts the actual velocity of the robot and chooses the motion direction. For obvious reasons, the collision avoidance routine must operate in real-time. Depending on the speed and weight of the robot, it is very important that the robot's dynamics (inertia and torque limits) are taken into account. The collision avoidance routine is easily trapped in local minima, such as U-shaped obstacle configurations. However, it reacts in real-time to unforeseen obstacles such as humans and is usually capable of changing the motion direction while the robot is moving.

3. PROPOSED SYSTEM MODEL

In our system model the microcontroller used as a processing unit. The sensor and web camera interfaced with the microcontroller. Web camera employed for monitoring the real world. The sensor can sense the environment, the machine learning can make use of the sensing information for automated navigation and obstacle avoidance in monitoring whenever the absence of user.[1]

The user can remotely monitor and controlling the robotic unit through the smart phone via GPRS. The web camera capturing video can streaming on the smart phone and control the movement of the robot by use of navigation button on the mobile app the robot can be selected by particular IP address of the robot (see the Fig 1).[5][6]

Whenever absence of user the robot can automatically monitor the environment by avoiding the obstacle and reach the destination through the machine learning approach by the decision tree learning algorithm [11]-[13]

Machine learning approach makes use of the decision tree learning algorithm to avoid obstacle during navigation automatically monitoring and reach the destination. [1]

ALGORITHM:

Algorithm: Decision tree learning algorithm.
Input: dynamic obstacles.
Output: avoiding obstacle.
Method:

```
initially robot (move);
sense ();
if (obstacle== true)
{
turn left;
sense ();
if (obstacle== false)
{
robot (move);
else
{
turn (direction == right && degree ==180^0)
sense();
if(obstacle==false)
{
robot(move);
}
else
{
turn(direction== right && degree==90^0)
robot(move);
}
}
```

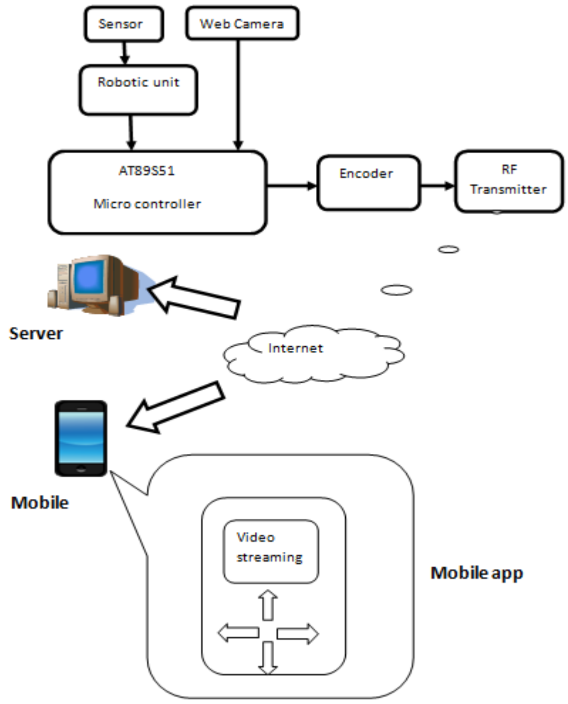

Fig 1: System Architecture.

3.1 Decision tree learning.

This decision tree learning algorithm avoids the obstacle during the navigation of the robot. The sensor value is boolean it can return true for the presence of the obstacle and false for the absence of obstacle. Initially robot moves in forward direction if the sensor senses the presence of the obstacle the robot turn left and sense if no obstacle present the robot moves along the direction else it can turn in right direction along 180^0 and sense again if the absence obstacle of the robot move along the direction else it turn right along 90^0 and moves along the direction[11]-[16].

3.2 Single operator multiple robots

In our proposed system single operator can control the multiple social robots (SOMR), in which single operator/user can control and monitoring the multiple and switching between them easily. [1]-[5]

The people can interact to the robot directly through the web camera based on the concept of social human robot interaction. For example the robot placed in shopping mall, museum the people/customer can interact with the robot for the route guidance. The operator or a user who operates remotely can response to the people through the robotic unit.

When the absence of remote operator the server can respond to people based the instruction stored in the database. This method of remotely monitoring the several places by a single operator.(see Fig 2).

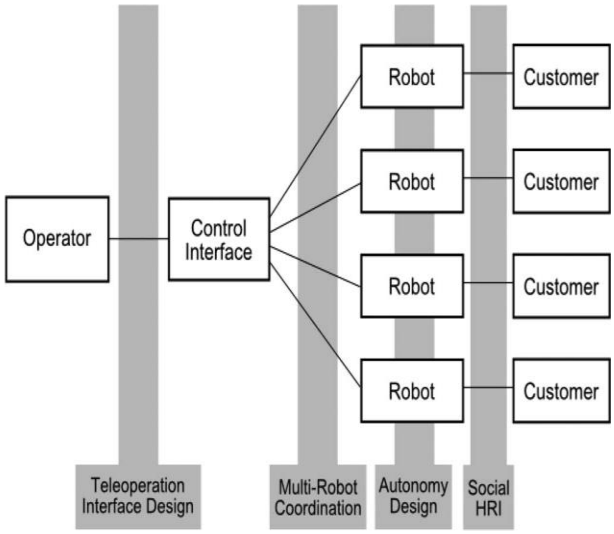

Fig 2: Single Operator controls Multiple Robots

3.3 Teleoperation interface design

An operator has two tasks to carry out: first, supervisory monitoring of all robots to recognize unpredicted situations, and second, support individual robots' recognition, planning, and actuation. Supporting both of these tasks provides a significant challenge for the user interface design.[1]

Both situation responsiveness and actuation necessities for the user interface differ for these two tasks as follows.

3.3.1 Controlling Individual Robots:

When controlling a single robot, the operator needs to be responsive of the robot's individual situation—with whom the robot is interacting, what that person is saying, and what the robot is doing. For simple systems, such as an information-providing robot in a shopping mall, this immediate information may be sufficient for the robot's communications. For more elaborate systems where the robot has a long-term relationship with the customer, long-term interaction history or personal information about that customer might be required.[6]

This interface also requires actuation controls for correcting sensor recognition, directing behaviors, and performing low-level control such as entering text for the robot to speak in uncovered situations.

3.3.2 Monitoring Multiple Robots:

When acting in a supervisory role and monitoring multiple robots, the operator needs to identify and react to unexpected problems in a timely manner. A outline of the state information about every robot should be accessible to the operator in such a way as to make errors and abnormal behavior easily recognizable.

3.4 Multirobot coordination

In this paper, we will model a robot's interaction as consisting of critical sections, where there is a high risk of interaction failure and thus a high likelihood that operator assistance will be needed, and noncritical sections, which can safely be performed autonomously. Critical sections tend to occur when the actions of the robot depend strongly on recognition of inputs from the customer, and thus the consequences of a recognition error are severe. Critical sections can also occur when there is a high probability that an uncovered situation will arise.

We consider errors in sensor recognition to be uniformly likely to occur in critical and noncritical sections. However, a recognition error is much more likely to result in interaction failure in a critical section than in a noncritical section. To prevent interaction failures, it is desirable for an operator to be monitoring a robot during critical sections[1].

A fundamental conflict arises when two or more robots compete for operator attention by entering critical sections at the same time. As noted above, social interactions are time critical. While the operator serves one robot, the customer interacting with the other robot is made to wait, which will have a negative impact on the quality of service, and possibly even cause failure of the interaction.[6]-[10].

4. IMPLEMENTATION RESULTS

Based on the proposed system model teleoperation on multiple robots through GPRS and obstacle avoidance using artificial intelligence approach the implemented results as shown in figures below. Implementations are based on the proposed system architecture and decision tree learning method.

4.1 Implementation results for automated monitoring

In Fig 3, initially robot moves in forward direction with the absence of operator.

Fig 3: moves in forward direction

In Fig 4, robot senses the obstacle and turns right and sense the environment.

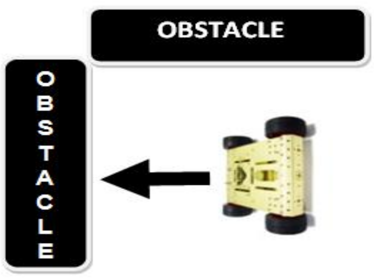

Fig 4: turn left and senses for the obstacle

In Fig 5, robot turns 180 degree right and senses for the obstacle

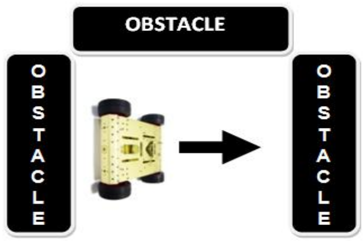

Fig 5: turns 180 degree right and senses for obstacle

Fig 6: turns 90 degree and move in forward direction

In Fig 6, the senses the obstacle and turn 90 degree right and moves the path it comes here no sensing needed because this the path it already navigated.

4.2 Implemented results for teleoperation on robot based on GPRS.

In Fig 7, the operator pressing the upper arrow on mobile application that instruct the robot to move in the forward direction. The communication between robot and user remotely through the GPRS.

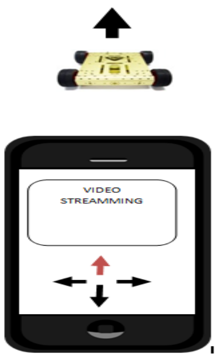

Fig 7: robot moves in forward direction

In Fig 8, the robot turn and moves in left when operator pressing the left button.

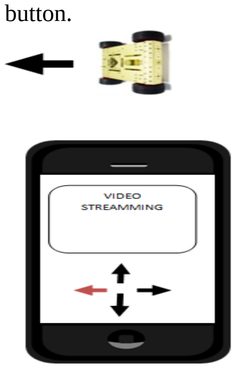

Fig 8: robot turn and moves left

In Fig 9, the robot moves in right when operator pressing right button.

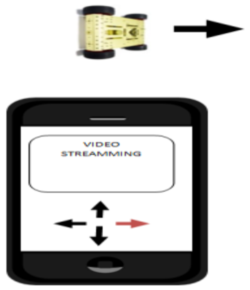

Fig 9: robot turns and moves right

In Fig 10: robot move in reverse direction when the operator pressing the down button.

Fig 10: robot turns and moves reverse.

5. CONCLUSION AND FUTURE ENHANCEMENT.

In this paper we presented a general framework to monitor and control the multiple robots remotely based on the GPRS and autonomous navigation and monitoring with absence of operator by avoiding obstacle through the artificial intelligence approach namely machine learning algorithm called decision tree learning. The web camera interfaced on the robot stream the captured video in the mobile. The machine learning can be done using sensors.

In future this navigation can be done GPS and teleoperation based on the advance technology. The robotic unit can recognize the people face and the interaction can be done most effectively and the automated route guidance can implemented on the robotic unit.

6. REFERENCES

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