Reducing Unwanted Handoff Using Machine Learning

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Abstract— Day by day the importance of internet and wireless technologies has been tremendously increases. As the cellular wireless communication techniques grow rapidly, the cells become smaller than the traditional communication system, then the handover events are very frequent and need to support a large number of users, and handover detection has become a very active research direction in a mobile computing environment. When the user moves from the range of one wireless area network to another wireless area network handoff will get occurs. Handoff is a very important of wireless mobile communication. The handoff algorithms provide gain, quality of signal (QOS). The two vital problems are raising in handoff, not necessary occurrence of handoff and handoff failure. To avoid these issues, an algorithm needs to be implemented to decrease the unnecessary handoffs and handoff failures. It minimizes the unnecessary handoffs and handoff failures by using algorithm when the mobile terminal senses the network of any wireless technology. This algorithm minimizes the unnecessary handoff and failures of handoff whenever predictive travelling distance in Wi-Fi (Wireless-Fidelity) cell smaller than the threshold value. Theoretical and simulation analysis of the algorithm shows that, travelling distance prediction based algorithm minimizes the probability of the occurrence of unnecessary handoff.

Keywords: Handoff, Wireless Networks; Mobile Terminal, Wireless-Fidelity, Machine Learning, Handover Detection

I. INTRODUCTION

Over the past 25 years a number of wireless communication networks have emerged for indoor areas. The assistance provided by these networks are geographically selective. As a result, a wireless communication terminal needs to connect to multiple points of connection and whereas networks as it moves from one location to another. The process of changing one wireless point of connection to another is referred to as handover or handoff.. When a mobile terminal moves away from a wireless point of connection, the signal level is going to decrease and there is a need to switch communications to another wireless point of connection. Handoff is the mechanism, due to that an ongoing connection between a mobile terminal and the network is maintained. .

Handoff can be categorized into two types:

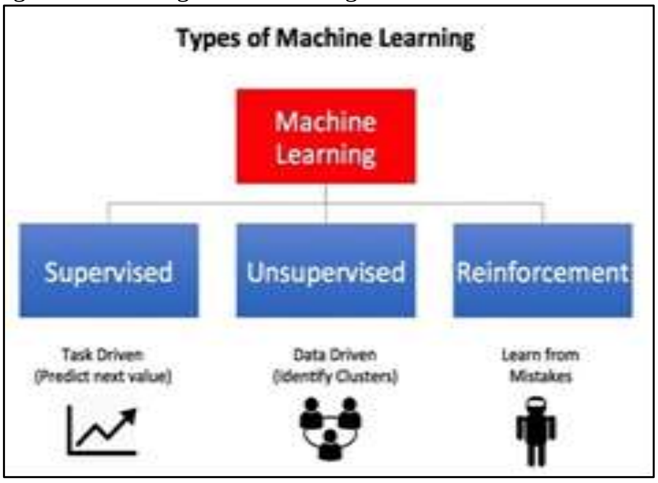
1) Hard handoff: the user’s connection to be entirely broken with an existing base station before being switched to another base station. It also known as Break before Make.
2) Soft handover: when a cell phone is simultaneously connected to two or more cells during a call. If the sectors are from the same physical cell site, it is referred to as soft handoff. It also known as Make before Break.

In order to guarantee the communication quality, the cell radius in modern cellular networks becomes smaller than traditional networks. The mobile user needs to frequently perform handover operations, and it is necessary to design a more efficient handover detection approach. The metrics of handover detection in cellular systems mainly include: carrier-to-interference ratio, distance between base stations and mobile terminals, signal intensity, etc. A reasonable and effective handover detection model has the following characteristics:

1) The drop rate is reduced and the number of mobile stations in a cell is allocated in a balanced manner by distributing the channels in a free cell to a busy cell;
2) reducing signal disruption in order to utilize the transmission channels;
3) implementing signal interconnection and intercommunication in heterogeneous networks in order to improve the communication capacity of channels;
4) Optimizing handover algorithms and reducing unnecessary handover rate in order to improve the utilization of channels. This study mainly focuses on the fourth point in order to optimize the algorithm model.

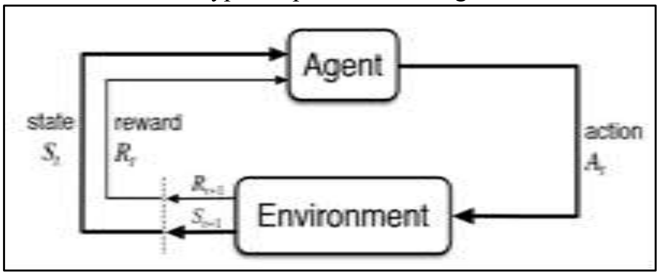
II. METHODOLOGY:

Machine Learning algorithm is using a training data set to create a model. When new input data is given to the ML algorithm, it makes a prediction on that basis of the model.The prediction is evaluated for accuracy and if the accuracy is acceptable, the Machine Learning algorithm is deployed. If the accuracy is not acceptable, the Machine Learning algorithm is trained the given/input data again and again with an augmented training data set.



III. REINFORCEMENT LEARNING

Here we mainly focused on Reinforcement learning. The objective of RL is to maximize the reward of an agent by taking a series of actions in response to a dynamic environment. Reinforcement Learning (RL) enables an agent to learn in an interactive environment by trial and error basis using feedback from its own actions and experiences. It's nothing but feedback oriented learning, feedback is of two types… positive and negative feedback.



IV. Q-LEARNING:

Q-learning is a model-free reinforcement learning algorithm. Q-learning is a values-based learning algorithm. Value based algorithms updates the value function based on an equation (Bellman equation).The 'Q' in Q-learning is stands for quality. Quality here represents how useful action should be given to gaining some future reward. Q-learning is an on - off policy learner. Off policy means seeks to find the best action for the current state. Q-Learning algorithm can dynamically fgure out the routing path by interacting with the surrounding environment which can be applied in a mobile ad hoc network. Based on forwardaware factor, proposed energy-balanced routing protocols for the WSN, which can be used in a mobile communication system to save the energy consumption.

In Q-Learning there is an interaction between agent and environment where the agent has to go through numerous trials in order to find out the best action. An agent chooses that action which has maximum reward obtained from its environment. The reward signal may be positive or negative depends upon the environment.

The Q learning algorithm work as follows:

Initialize $Q(s,a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Repeat (for each step of episode):
    Choose a from s using policy derived from Q
    Take action a, observe r, s'
    Update
      $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
    $s \leftarrow s'$;
  Until s is terminal

V. PROPOSED WORK:

The main steps of handover decision in communication systems include:

1) Frstly, design wireless network ;
2) Secondly the decision system determines the quality of communication to a mobile user or other terminals;
3) Third one , it executes the handover detection algorithm and chooses the target cell to be switched to;
4) And lastly it executes the handover operation by using machine learning (consideration all the factors including the coverage area of a base station, the staying time of a mobile user and other important factors which could afect the movement of users.)

VI. SIMULATION RESULT

The network animator (NAM) is used to visualize the simulations. After simulation, NS2 outputs are either text-based or animation-based simulation results. For interpreting results graphically and interactively, NAM (Network Animator) and XGraph tools are getting used. The result of the trace file that can be for data processing (calculate delay, throughput etc) and to visualize the simulation with a program called Network Animator (NAM). NAM is a visualization tool that visualizes the packets which are propagate through the network. Most of the analysis required for the wireless environment can be easily figured out with the various types of .awk, .xg and trace or the .tr file. The graph files are easy to understand and the tool helps to get the values of the various complicated QoS values with a ease.

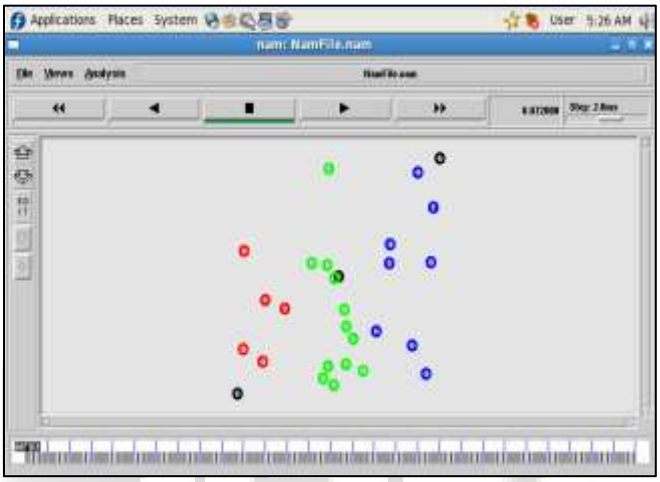


Fig. 1: NAM Simulator

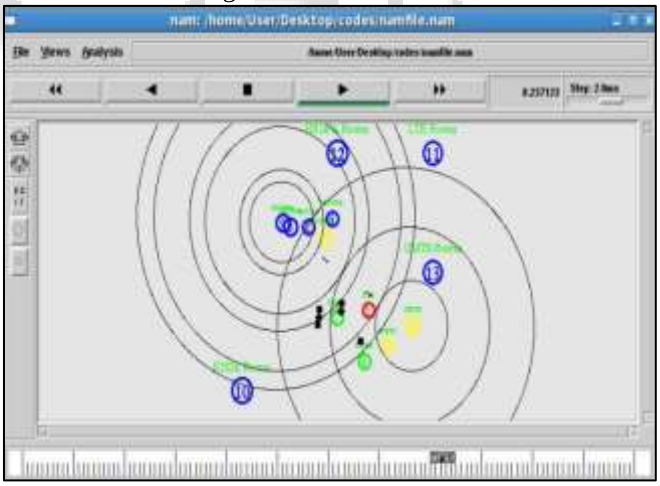


Fig. 2: Communication between nodes

The figure 2 is communication between any two nodes. When nodes are moving from 1 network to another network, the communication between 2 nodes as shown in figure. And there is small amount of packet drop is also present.

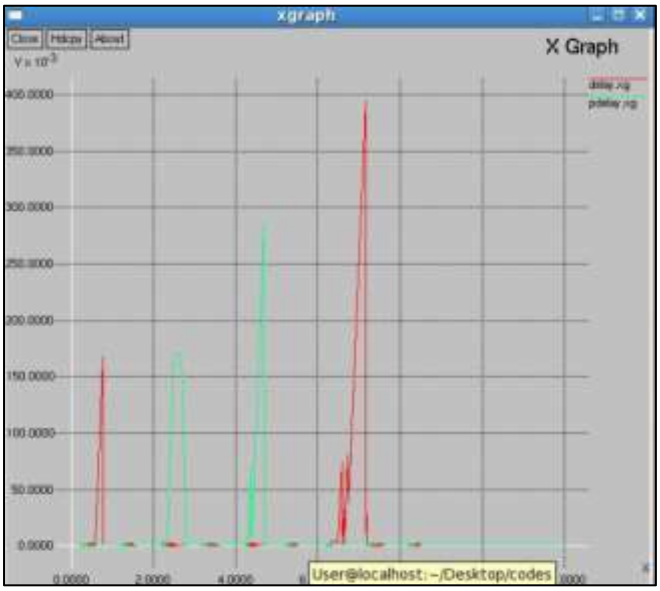


Fig. 3: Delay graph

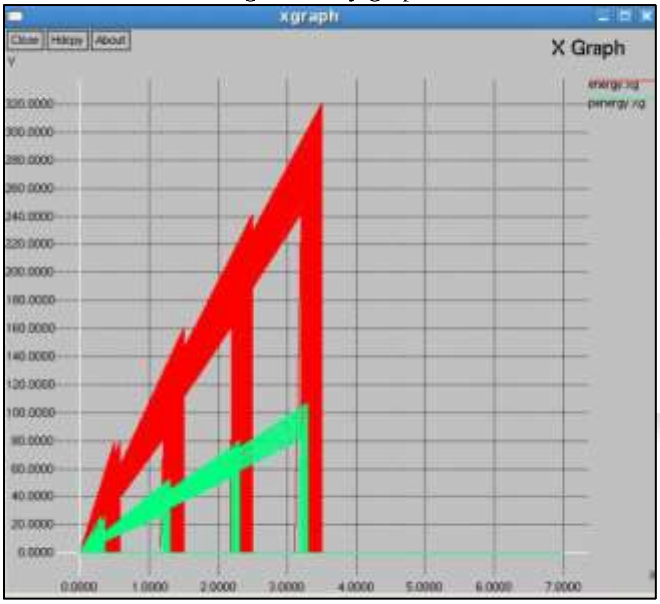


Fig. 4: Energy graph

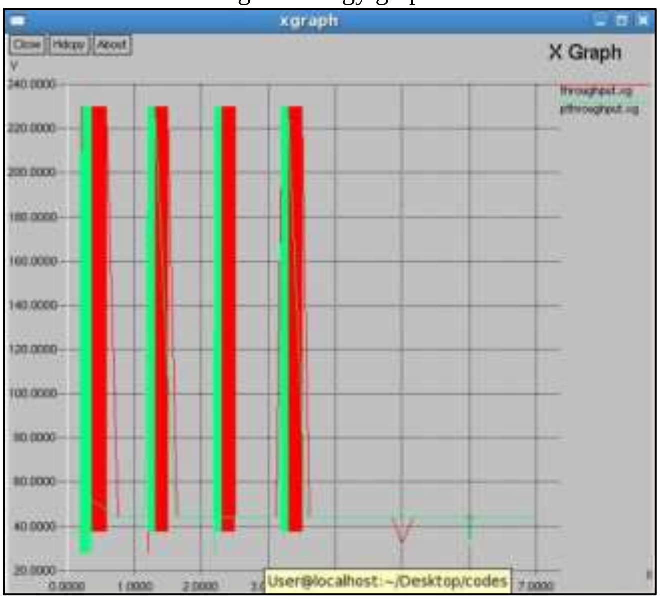


Fig. 5: Throughtput graph

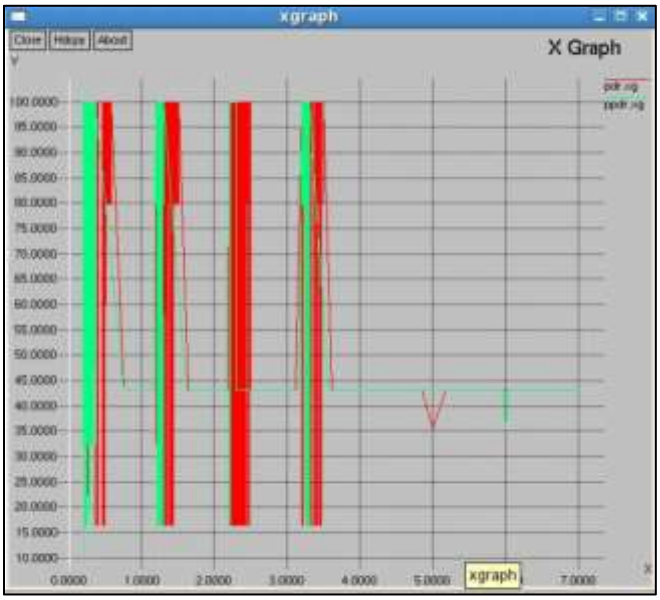


Fig. 6: Pdr graph

From the above result we conculde that as number of node is increases, we get better output. At higher number of nodes we get high Throughtput and PDR with acurate delay and energy graph. The prediction delay (pdelay) should be small ,and prediction energy (penergy) should be low to increase the battery performance.The jitter should be high for better network packet consistency ,the pdr is also high for better quality purpose , due to high pdr the dropping is as low as possible.

VII. Conclusion:

In this paper a method to optimize the handoff in wireless networks was presented. This method divided into two sections: calculation of travelling distance and the threshold calculation. The travelling distance prediction and threshold calculation done for some parameters like handoff failures and unnecessary handoffs in wireless networks. Compared the travelling distance prediction based method with RSS based method, and concluded that the travelling distance prediction based method minimizes the number of unnecessary handoffs and failures of handoff more than RSS based method. Results show a reduction in handoff probability of 32% and a reduction in number of handoffs by more than 10% when compared to standard algorithms, which can be used as a base point for other algorithms in future comparison

VIII. Future Work

Furthermore, researchers can work on security of the proposed machine learning based handoff system, and try to integrate block chains and other state of the art encryption techniques in order to make the system more efficient in terms of security of the network.

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