Handover Improvement using O-RAN Near-RT RIC for Network with Coverage Hole

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Abstract: Handover is very crucial in cellular communication since it may interrupt data transmission. The traditional handover algorithm works well in ideal conditions, but it may fail in certain conditions such as coverage holes. In this letter, we present our simulation to improve handover performance using machine learning. We implement and perform novel modifications on Near-RT RIC, a new network element by O-RAN, to solve the target cell decision problem using a machine learning algorithm in a network with a coverage hole. We show that this solution is proven superior to the traditional handover algorithm.

Keywords: cellular, handover, machine learning, O-RAN

Classification: Network management/operation

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1 Introduction

In cellular communication, handover can be defined as the process that prevents ongoing communication from getting interrupted as the mobile equipment changes its attachment point (i.e., cell). Handover usually takes place when the user is physically moving along the network. During this process, there is a possibility of data loss due to temporary interruption of transmission. Therefore, a robust handover algorithm to determine the target cell is very important to avoid data loss.

The traditional handover algorithm assesses serving and neighboring cell measurement reports. The target cell is usually determined by the strongest or best-quality neighbor cell. This algorithm is usually reliable in ideal conditions, where RSRP (signal strength) and/or RSRQ (signal quality) can represent the reliability and quality of the target cell. This ideal condition can be achieved if the propagation path of the cell is even and homogenous, therefore the radio condition is always predictable solely by the RSRP/RSRQ measurement.

However, in some non-ideal conditions, this traditional algorithm may cause problems. In a condition where the radio propagation is disturbed by reflection, refraction, and/or attenuation such as the presence of an obstacle, the cell condition will not be predictable by RSRP/RSRQ measurement only. This may cause an unusually strong or weak signal in an unexpected area. Using a traditional handover algorithm, this condition causes an incorrect target cell.

Our research uses a machine learning algorithm to perform target cell determination. Using Near-RT RIC, the algorithm can be implemented modularly without major modification in the base station. We also show, using simulation results explained in Section 5, the effectiveness of this proposed method to improve handover performance. The result shows that the file download success rate during handover is 86.2% (with the traditional handover algorithm), and 92.7% (with our proposed method), using 25 training data. For a larger number of training data, the improvement of our proposed method is even better.

2 Simulation Design

We simulated a non-ideal network by creating a coverage hole where the RSRP measurement is not reliable to determine the target cell. In the case of a coverage hole, where the signal is obstructed by objects, the traditional handover algorithm may result in a wrong target cell. For example in Fig. 1, when the user enters a coverage hole of Cell 2 just after handover to Cell 2, it may lose the connection. However, if the user was handed over to Cell 3, it may still be connected.

For our first simulation, we performed this simulation using NS3 LTE network simulator[1] based on previous studies[2]. NS3 LTE network simulator can simulate a network environment by specifying the base station positions, properties of the cells, and the UE movement behavior using a Linux-based
application. We ran simulations with the UE moves with random trajectory angles, and the handover target cell was forced to Cell 2. Next, we did other runs with the target cell being forced to Cell 3. We noted down the state of the UE file download process, whether successful or not, and record the RSRP measurements. These runs of deterministic handover cases (to each cell) are used as our training data for our second simulation. After this, we ran other simulations with a non-deterministic handover case, where the target cell is determined by a traditional handover algorithm. We used the state of the download process in this simulation data as the result of our first simulation. The RSRP measurements of this data will be used as test data in our second simulation.

For our second simulation, we used the training data and test data obtained in our first simulation. We put these into the database of Near-RT RIC which will be further explained in Section 4. This Near-RT RIC determines the target cell using a machine learning algorithm and we can compare the rate of successful download with the traditional handover algorithm done in the first simulation.

3 O-RAN Near-RT RIC

Due to the benefit of machine learning, a lot of studies try to incorporate it into the cellular network. However, the implementation requires a major change in the existing network elements.

Open Radio Access Network (O-RAN) Alliance[3] is a worldwide consortium with the mission to reshape RAN to be more intelligent, open, virtualized, and fully interoperable. O-RAN is standardizing some new network elements to host machine learning algorithms so they can be implemented in the network without any major change in the existing network elements. These network elements are called Radio Intelligent Controller (RIC), comprising Near Real-Time (Near-RT) and Non-Real-Time (Non-RT) RIC.

Near-RT RIC hosts applications that require quick response like mobility
management and is installed on an edge cloud platform. Non-RT RIC does not necessarily require a quick response and may be installed on the existing Network Management System.

4 Anomaly Detection Use Case

The software for mobility management use case is published openly by O-RAN Software Community[4] as the Anomaly Detection Use Case (Fig. 2). This use case is a collection of applications (xApp) to provide the best connection by detecting anomalies in user connection quality, and performing handover if necessary.

The Anomaly Detection xApp is detecting anomalies in the UE connection (e.g. RSRP degradation). This anomaly is reported to the Traffic Steering xApp and it triggers a query to the QoE Predictor xApp. The QoE Predictor xApp will predict the quality (i.e., throughput) of each target cell in the network and report back to the Traffic Steering xApp. Finally, Traffic Steering xApp will take action based on the result from QoE Predictor xApp, e.g. handover to the cell with the best (predicted) throughput.

The problem with the original software is, that the training data used by QoE Predictor xApp to predict throughput doesn’t reflect the UE movement since it only contains the monotonic change of cells throughput. To fit with our research, we redesigned the database and modify the training data. We also changed the software design by putting RSRP measurements into account.

We performed novel modifications on the QoE Predictor xApp to fit our research needs. In the original software, the xApp queries from the training data to get the throughput over time for each cell. We modify this by adding an RSRP element to the training data and the query. Therefore, the xApp
will query the training data to get the throughput over time for each cell, but only the ones where the RSRP measurements are similar to the one reported by the UE. We also remove the outliers of the query result to get more reliable data. From this query result, the xApp will predict the next throughput of each cell using the vector autoregression method.

This modification is proven usable to predict the cell throughput while putting RSRP measurements (thus UE movement) into account, unlike the original software. Therefore, the target cell prediction depends on the UE trajectory angle.

5 Simulation Result

We ran two simulations: traditional handover using NS3 and machine learning-based handover using Near-RT RIC. The result of the first simulation shows that 86.2% of the file downloads are successful if the UE performs handover using a traditional algorithm. This was caused by the presence of a coverage hole in Cell 2. The UE that was handed over to Cell 2 lost its signal and could not finish the download.

In the second simulation, we determine the target cell using Near-RT RIC. The amount of successful downloads if using Near-RT RIC is significantly higher compared to the traditional handover algorithm (Fig. 3).

![File Download Status](image)

Fig. 3. Simulation Result Comparison

However, if we didn’t modify the Near-RT RIC software, the QoE Predictor xApp is not suitable for our simulation scenario and cannot predict the target cell properly. The original Near-RT RIC only provide 45.2% download success rate as the UE in all of the simulations was handed over to Cell 3. This is because the original software only determines the target cell based on the UE position and doesn’t care about the UE movement. We modified the software by putting the RSRP measurement into account to predict the throughput in each neighbor cell, therefore considering the UE movement not
only the UE position. Finally, we can get better results with the modified software.

We also investigated the impact of training data amount to the target cell prediction performance. If we use 100 training data 95.3% download cases are successful. If we reduce the training data to 50, the success rate is decreased but still considerably high (94.1%). And even if we reduce the training data to 25, the success rate is still better than the traditional handover algorithm (92.7%).

6 Conclusion and Future Works

In this letter, we present our simulation to show that machine learning-based handover can provide better results in a non-ideal network environment, in this case: the presence of a coverage hole. We also show that the machine learning algorithm in RAN can be implemented using Near-RT RIC to avoid major modifications in the existing network elements. Some novel modifications were also performed to the original Near-RT RIC software to improve the handover performance.

For our next research, we will develop the machine learning algorithm using other methods, such as a neural network or reinforcement learning, to improve the vector autoregression used in the original software. We will also plan to test the proposed method to adapt to a more generic environment other than the coverage hole case.