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Building a Robust RTK-GNSS Infrastructure with Seamless Handover and a Multipath Detection Approach

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Abstract - RTK-GNSS is a promising positioning technique to achieve centimeter-level accuracy. In this technique, a stationary base station plays a vital role in correcting the positioning results of a movable user receiver; however, the base station correction signals are often interrupted, or delayed due to single-base line area, hardware biases, environmental factors, and multipath errors. Therefore, we propose three major new components to improve a user receiver's positioning accuracy and precision. The first component detects the status (i.e., healthy or unhealthy state) of the base station through the internet. The second component assigns the most favorable base station from multiple base stations in a seamless approach. The final component detects the multipath signal using a machine-learning classifier model. After analyzing the experimented results, our approach maintained the rover receiver positioning accuracy within the centimeter-level even after the base station handover. Similarly, in multipath detection, around 98% of NLOS and around 95% of the LOS signals are correctly discriminated. By combining all three components, we achieved high reliability of RTK-GNSS positioning in different areas by using continuous correction signals from the base station and considering only the visible satellites.

Keywords: RTK-GNSS, Seamless handover, Web-based monitoring, Reliable infrastructure, Multipath detection

1 INTRODUCTION

Global Navigation Satellite System (GNSS) is an active research area for navigation, mapping, positioning, and many other areas that need monitoring and controlling their location-based services. In the conventional single-point positioning system, the user's position can be instantly determined using a pseudorange between the satellite and the user's receiver. For this, the receivers need a signal from four or more satellites. In this single-point positioning, the positioning accuracy ranges from 10m to 30m, as various factors caused errors in the GPS observation [1]. However, many applications, including autonomous driving and flying, precision agriculture, and weather forecasting, require centimeter-level accuracy, which is called precise positioning. Therefore, we need advanced positioning techniques to provide highly accurate positioning and navigation functionalities in those applications. One of the famous differential positioning systems is the Real-Time Kinematics-Global Navigation Satellite System (RTK-GNSS).

A higher resolution distance information called a phase pseudorange is used instead of the code pseudorange. As shown in Fig. 1, the precise position, also called fixed position, of a rover receiver, i.e., user receiver, is calculated through the received signal from satellites and the correction signal from the base or reference station.

However, rover receiver position accuracy is degraded severely because of the interrupted, delayed, or discontinuous base station's correction data as well as communication link. In this differential system, correction data from the base station is affected by a number of factors: such as coordinate errors, environmental factors, the reflected or diffracted signals, which results in a less accurate position (i.e., within a few meters of accuracy), called a float solution.

Therefore, challenging environments, including snowy, mountain, forest, and urban areas, are crucial for precise positioning in RTK-GNSS. Errors that occurred due to these factors are extremely difficult to solve through differential correction techniques. For instance, the precise positioning applications like the drone carrying medicines and equipment service, aiming to provide medical care to the remote mountain communities and precisely measuring the altitude of the mountain, including Mt. Everest, is the subject of attention in the Himalayan country, Nepal [2], [3]. Similarly, applications like precision agriculture, mapping, and survey, weather forecasting are gradually increasing in many countries.

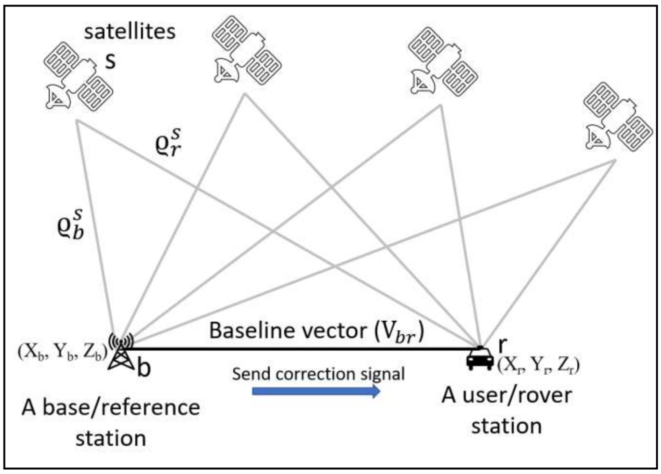

Figure 1: Principle of differential positioning

However, service disruption and false assumptions caused by different error factors in the base station may lead a rover receiver to use unreliable correction information from unhealthy base stations. As a result, it will mislead the rover receiver as well as degrade the reliability and accuracy of the base station data.

Furthermore, the base receiver's differential correction signal is valid for the short-baseline range only, i.e., generally considered the area within 10km. Therefore, the conventional RTK technique is inefficient and cannot ensure the continuity of the GNSS signal for a moving object that may operate beyond a base operating range. Besides, no redundancy of the base station is usually available if the active base station experiences any malfunctioning or hardware bias errors.

On the other hand, satellite positioning is still challenging in urban areas due to signal reflections by buildings or skyscrapers, so-called multipath error. As a result, positioning accuracy is severely degraded.

Therefore, focusing on those errors factor of snowy areas and multipath areas, this paper presents a modality of a robust RTK-GNSS infrastructure that guarantees continuity and reliability for precise positioning.

This paper is divided into seven sections. After the first introductory section, the second section clearly describes the problem statement, where we discuss the necessity of this research work. Section 3 gives a brief overview of the past researches and the preliminary works. Section 4 is an important section, where we discuss the system approach with theoretical dimensions of the research. Section 5 and 6 describe the design, methodology, working principle, characterization, result, and evaluation of this research. Finally, the last section of this paper gives a brief conclusion.

2 PROBLEM STATEMENT

The reliability and continuity are major concerns in RTK-GNSS, even though it is widely used in various applications. Notably, while doing RTK-GNSS experiments in dense snowfall or high buildings areas, various limitations were encountered. Therefore, to address the specific problem through a new approach, the authors mainly focus on three dominant problems that should be addressed for continuous and precise positioning.

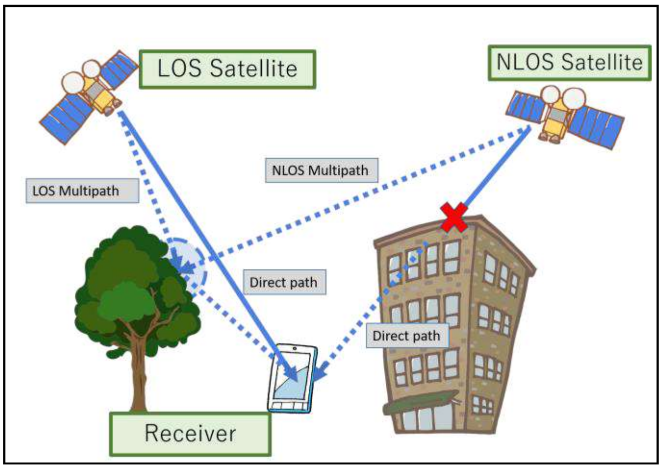

Figure 2: Multipath signals

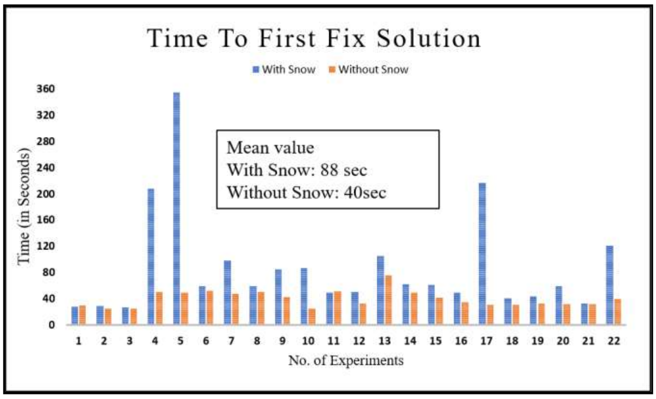

Figure 3: Snow effects in time to first fix solution

2.1 Unknown Status of The Base Station

Any problems or errors in the base station affect the corrective signal used to calculate the rover receiver's precise positioning. For example, in the mountain or snowy area with the uneven landscape, hard frost weather, and chances of heavy snowfall, landslide, earthquake, and volcanic eruption caused significant errors. Mainly, when the bunch of snow covered the base station's antenna, the signal strength was degraded because of the multipath error induced by the snow surface [4]. Also, if the coordinate of the base station changed because of landslides or by other factors, the positioning accuracy of the rover receiver would degrade due to the inaccurate base station's coordinate. Similarly, if the running base station experienced any malfunctioning or hardware errors, no redundancy solution would be available to detect the base site's status from the rover end. In addition, when the base station interrupted by some errors, the recovery time was often several minutes or even a few hours. Hence, the rover receiver ends up using a correction signal from that unstable or unhealthy base station. As a result, positioning accuracy is severely degraded.

On the other hand, if there is no correction signal from the base station, we need to visit the actual field to confirm a base station's state; however, this is not a cost-effective, reliable, and appropriate solution for real-time applications. Therefore, ensuring the data continuity and reliability of the base station under challenging environments is very important.

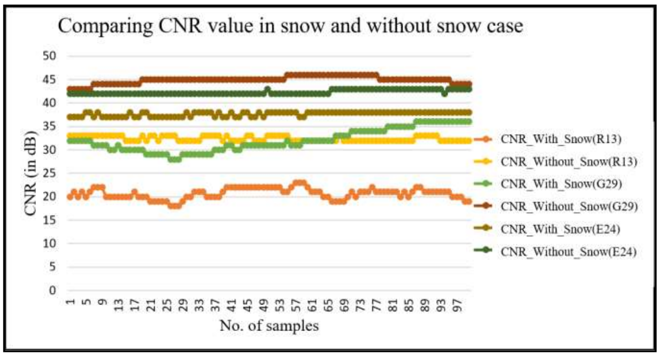

Figure 4: Snow effects in Carrier to Noise Ratio

2.2 Limitation of Base-to-Rover Operating Range

In the conventional RTK-GNSS, the base and the rover station need to operate in the same environmental area (i.e., generally considered 10km from the base station). Beyond this range, distance errors and atmospheric conditions at the base and the rover receiver may significantly vary. These error factors cannot cancel out through differential processing. Therefore, the base station data outage is one of the major concerns, particularly for the moving object. In the past few years, many researchers have proposed a multi-network base station adjustment process for the wide area [5]; however, those methods are challenging to implement in the actual field and for a smooth handover, i.e., handover to another base station without dropped signal. Thus, to provide a continuous correctional signal in a wide area for a moving object, the authors are concerned with this problem.

2.3 Multipath Error on The Rover Receiver

GNSS satellite signals are subject to reflection and diffraction, like any other type of electromagnetic wave. Therefore, in an urban area where the grounds are surrounded by tall buildings, skyscrapers, or trees, the rover receiver often faced multipath error. Notably, the reflected or diffracted signal from those objects causes multipath errors. In general, the receivers receive both direct and reflected (or diffracted) signals. As the multipath signal takes a longer path than the direct signal, an error was caused in pseudorange measurement, which severely degrading the GNSS accuracy to several meters [6].

There are mainly two types of multipath signals: Line of Sight (LOS) multipath signals and Non-Line of Sight (NLOS) multipath signals, as demonstrated in Fig. 2. For LOS multipath error, various signal correlation techniques were proposed to mitigate or minimize the LOS multipath signal by many past researchers.

However, there is no reliable technique for the NLOS multipath. Also, it is more crucial than LOS multipath signals because of the reflected signals. As a result, a broad range of positioning errors happens. Hence, NLOS multipath detection and mitigation techniques are required.

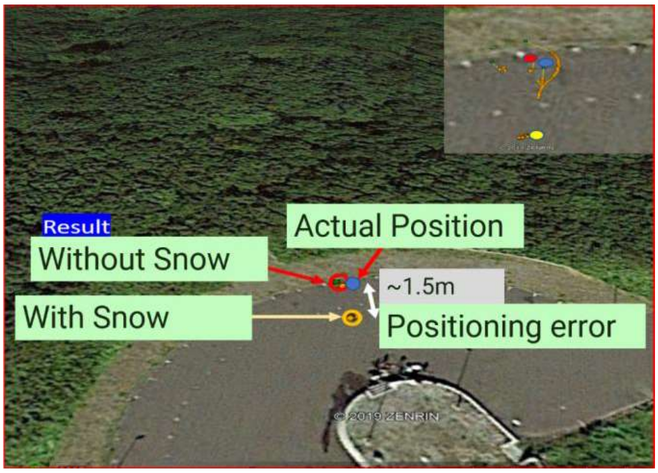

Figure 5: Positioning error caused by Snow accumulation

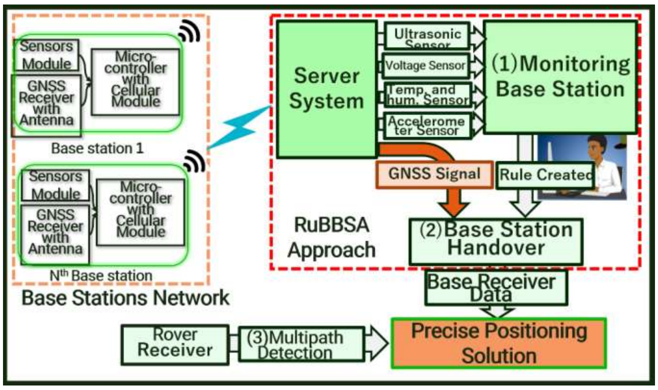

Figure 6: System architecture

In summary, to increase the overall performance and build a robust RTK infrastructure in the mountain and urban areas, multi-base stations with seamless handover mechanisms and NLOS multipath detection mechanisms are essential parameters.

3 BACKGROUND

3.1 Preliminary Research

Our preliminary research proposed a cost-effective and reliable system that overcomes the conventional RTK-GNSS infrastructure to enhance positioning solutions [7].

The goal of that research was to evaluate the low-cost receiver's capability in the harsh receiving condition (such as challenging weather, multipath, obstruction, etc.) and find the major problems that happen in the base site [8]. Therefore, we conducted our experiment in two different weather and geographical regions to demonstrate positioning accuracy, reliability, and feasibility of the system's architecture.

Nonetheless, the major problem encountered while doing an experiment in the heavy snowfall region.

The snow accumulation problem, the signal strength, and time to first fix solution (TFFS) are negatively affected, as shown in Fig. 3. Here, TFFS means the time need to get the first fix solution from the float solution. Similarly, a significant difference was found while comparing the value of Carrier to Noise Ratio (CNR) between snow and without snow state, as shown in Fig. 4. The difference of carrier to noise ratio is more than 8dB because of the reflected or a diffracted signal when the snow height on the antenna is around 15cm.

In the second experiment scenario, we have done our experiment where GNSS signals are often obstructed by buildings leading to reflected and diffracted signals. The observation shows the tendency of a drop in SNR when the receiver is in the multipath environment. SNR measurements are smoother when the receiver is in an obstruction-free environment, as shown in Fig. 5.

We concluded that conventional RTK-GNSS is still insufficient to provide continuous, reliable, and precise positioning in those areas from these experimental scenarios and results. Thus, this research focused on cost-effectively building a robust RTK-GNSS infrastructure.

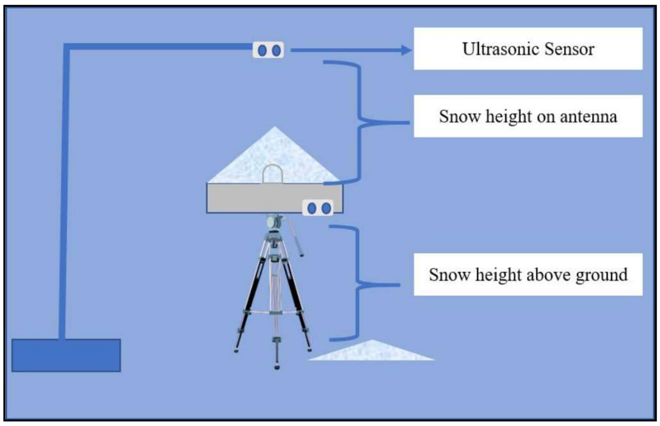

Figure 7: Snow height measurement scenario

3.2 Related Research

Several previous studies enhance the reliability and accuracy of the RTK-GNSS technique using different methods. In RTK positioning, the rover receiver needs to work within a base operating range, which is a major constraint for a moving object that works beyond the operating range. Therefore, many networking techniques that use multiple base stations were practiced in recent years. Some of the networking techniques are Master-Auxiliary (MAC), Virtual Reference Station (VRS), Pseudo-Reference Station (PRS), which operate with multiple base stations and provide precise positioning [9]. Quan et al. proposed a Network RTK system using observations from numerous continuously operating base stations [10]. Similarly, VRS based RTK system was also proposed to provide continuous observations in Malaysia [11]. However, these methods are challenging to implement, need active communication links, demanding control center operation, stability issues, and expensive operating costs. Also, a continuous handover could be the limitation of these Network RTK systems. Generally, accuracy drops to float solution from the fixed solution in the handover process.

Similarly, to mitigate the NLOS multipath error, it is crucial to identify the NLOS signal from all received GNSS signals. A new research stream dealing with multipath detection utilizes an additional sensor, 3D mapping, or image processing technique. Suzuki et al. proposed a fisheye camera and omnidirectional infrared camera techniques to detect multipath signals [12]. However, these detection techniques are affected by weather, light conditions. The method of integrating multi-sensors might be helpful in some conditions but could not solve entirely.

Also, a laser scanner to differentiate visible and invisible satellites was proposed by Maier et al. [13]. Also, multipath detection using 3D maps and Aerial LiDAR data were also practiced in few researches [14]. However, these were complicated to apply for the moving object and challenging to integrate in real-time. Some researchers worked on multiple GNSS signal correlators in a software GNSS receiver; however, it is challenging to design a special correlator in the practical field effectively. Therefore, to address the station-based errors and the base station handover issue, we felt the necessity of reliable, smoothly operable, easily applicable, and cost-effective RTK-GNSS used in different places and scenarios, including Himalayan and snowy regions.

Thus, we have primarily done our research [15] to analyze the system architecture and introduced the handover scheme and multipath detection approach in this research paper.

4 SOLUTION APPROACHES

This section explicitly describes our approaches to solving conventional RTK-GNSS, especially in mountain/snowy areas and urban areas, as shown in Fig. 6. Firstly, to know the base station's status from the rover side (as described in subsection 2.1), we proposed a base station monitoring system such that an unhealthy base station could be detected in the rover end. Secondly, we proposed a seamless handover mechanism with a multi-base network to solve the single base-rover range problem (as described in subsection 2.2). Finally, to solve the multipath error on the rover receiver (described in subsection 2.3), we proposed LOS and NLOS multipath detection mechanisms. The detailed explanations are as follows:

4.1 Detecting an Unhealthy Base Station

The first approach is knowing the base station's status from the rover end in real-time. When different limiting factors obstruct the base station, the correctional signal from that base station consists of many errors. As a result, the positioning solution in the rover receiver degraded. Therefore, to make a proper decision and constant alert for future trouble prevention, we proposed detecting unhealthy base stations through the internet. Different kinds of sensors require in this proposed system. For example, we used ultrasonic sensors and accelerometer sensors, which are used for snow height measurement and antenna movement detection, respectively.

After collecting data on the server, sensors' data are used for two purposes: web-based monitoring and the optimum base station selection process. Here, we proposed a web-based base station monitoring technique to monitor the base station's status manually. Sensors' data are visualized on a web page and monitored from anywhere, provided that an internet connection is available. Similarly, a handover process is needed for the kinematic rover receiver beyond a base station's baseline area.

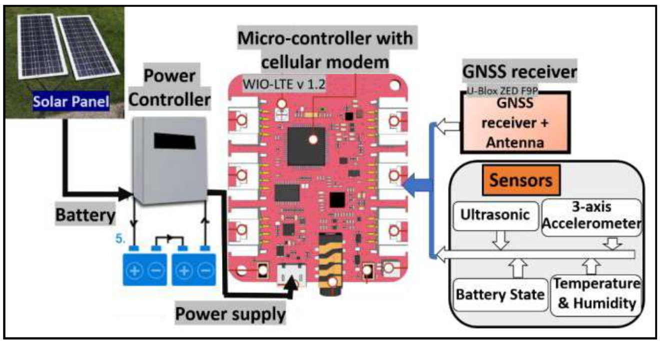

Figure 8: Block diagram of the base station

In such conditions, the optimum base station (i.e., a favorable base station among available base stations) is needed in the rover receiver to calculate precise positioning. Therefore, the base station's sensors data are used with the base-rover range to detect the base station's state. If the particular sensor data is less than the respective threshold value, the base station is considered unhealthy. For instance, the threshold value of snow height is 5cm because the signal strength is decreased faster after that height. For a reliable system, the physical hardware and data processing method also have a significant impact. Therefore, we proposed compact hardware and reliable data processing.

4.2 Seamless Handover

The second component is a processing component, an algorithm specially designed to assign the most favorable base station from the list of multiple base stations in a seamless manner. To achieve precise positioning, we proposed a Rule-Based Base Station Assignment (hereafter, RuBBSA) algorithm. In this algorithm, the rule is based on two major factors: sensors' value and the distance between the rover receiver and the corresponding base station (explicitly explained in section 5.5). The first rule ensures that the sensor's measurement is used to monitor the base station's physical condition, such as snow accumulation, battery power supply outage, and the base station's coordinate. The second rule ensures the operational range of the receiver.

For instance, when the user moves out from the functional baseline area and or conditions when the base station cannot send differential correction information to the rover receiver, this algorithm assigns a new base station. This processing of choosing an optimum base station from multiple base stations is the main target of this algorithm. The next available optimum base station is assigned by the proposed algorithm seamlessly and dynamically.

We used two RTK engines on the rover side for this handover process. In the RTK system, fixed positioning solution is obtained by using carrier-phase measurements rather than just pseudorange. However, the processing of carrier phase measurements is subject to so-called carrier phase ambiguity, an unknown integer number of times the carrier wavelength that needs to be fixed. The ambiguity resolution, which is the crucial factor for precise positioning, is the process of resolving the unknown cycle ambiguities of double-difference carrier phase data as integers. There are mainly three steps to determine ambiguities resolution: estimating float-valued ambiguities, finding the best integer ambiguity set, and validating the best ambiguity set. After validating the ambiguity set, a fixed solution is calculated in the RTK engine. However, when one base station is changed to another base station in the same RTK engine while doing handover, validating the ambiguity set is difficult. Only float-valued ambiguity occurred for few seconds. As a result, the positioning solution is dropped into a float solution. Therefore, to make a handover without losing the fixed positioning solution, two RTK-engines are needed. Thus, the proposed mechanism has two RTK-engines to provide continuous and precise positioning.

4.3 Multipath Detection

In order to increase the positioning accuracy of the rover receiver in a multipath environment, this research also aims to develop a multipath detection technique. Here, multipath detection proposed by using different satellite signal features by differentiating LOS signal and NLOS multipath signal. In the last decade, many methods have been proposed to detect multipath signals. Most of the research focuses on a single-point conventional positioning system by using different algorithms [16], [17].

Only one receiver is used to calculate its own position in single-point positioning; therefore, differentiating LOS signals and NLOS multipath signals are comparatively more straightforward. However, we need to consider the rover and the base station's observation data in the RTK-GNSS technique. Therefore, to classify the LOS and NLOS multipath signals with high accuracy, we proposed a machine-learning-based classifier that can differentiate LOS signals and NLOS multipath signals using significant features values.

Here, the kernel-based support vector machine (SVM) classifier is used to differentiate multipath signals. It is essential to train our data with accurate classification because, based on the training data, a machine learning model learned the features and predicts the output accordingly. Based on the characteristic of CNR, which says that the signal fluctuates under static conditions; thus, the differential CNR value (i.e., the difference between base CNR and a rover CNR value) has been used to detect NLOS signals. These featured values are applied to the training process in machine learning.

5 METHODOLOGY

5.1 Building a Compact Hardware

This research has been conducted by building a base station prototype module consisting of a GNSS receiver with antenna, micro-controller, and sensors network. In the rural and the Himalayan region, the continuous power supply is one of the significant problems. Therefore, a solar energy source- an easily movable, self-sustainable, and reliable power source- is used. A micro-controller called Wio-LTE is used to process GNSS receiver and other sensors data, which is a prototyping development board with LTE(4G) communication version of Wio Tracker (Wireless Input-output) that enables faster IoT GNSS solutions [18]. To monitor each base station's physical condition, we used various sensors modules in respective base stations. For instance, ultrasonic sensors are used to predict the base antenna's snow height, as shown in Fig. 7.

During this process, temperature fluctuation affects the transmitted sound wave from an ultrasonic sensor. Thus, the temperature sensor is used to correct the temperature-related distortion of the measured value. Also, to precisely monitor the base station coordinate, we used a 3-axis digital accelerometer sensor that detects orientation, gesture, and motion in case of natural disasters. Besides that, to check battery voltage level and charging level, a battery state sensor is used. To make a compact hardware system, all sensors are connected to the microcontroller board that consists of a cellular modem, as shown in Fig. 8. All data are sent to our server system in real-time. The base station antenna is fixed correctly in the accurate position.

Similarly, to overcome the multipath errors and fully receive all visible satellite signals, the antenna is placed in an open sky environment such that all satellite signals are received as a Line Of Sight (LOS) signal. This compact infrastructure consumes deficient power. The base station system needs 600mA to 2A current with a 5V power supply at regular communication, making the system operation longer.

Moreover, the system consists of a low-cost receiver and digital sensors. The total cost is around $1500. In contrast, survey-grade receivers cost around $10,000, for instance. Therefore, our system can be comparatively cost-effective, movable, and easily installable in regular and challenging weather areas.

5.2 Data Processing and Management System

In our proposed system, collected sensors data from each base station is sent to the server system through the internet connection. Here, we need a proper and continuous communication link between a base station and a user receiver for the real-time application. Therefore, we should select effective communication to provide reliable internet connection continuously. Considering those factors, including operational cost, maintenance cost, and the number of computations needed by the rover and the processing center, we found that a cellular modem is one of the appropriate methods in the mountain region. We used cellular connectivity Soracom, which provides the IoT network platforms [19].

JavaScript Object Notation (JSON) format is used to transmit these data in web-based applications such that those data could be displayed on a web page correctly. The time-series data shows the base station's past conditions and present conditions, such that the changing state is visible and easily compared to the respective sensors' threshold value. Thus, detecting unhealthy base stations is done before assigning a base station in a rover receiver. The web-based graph is plotted on the web browser, which shows that each sensor's data is being updated with time-lapse. This process of monitoring the actual state of data is adequate, especially when the base stations' knowledge is manually needed for the assignment process.

5.3 Determining of an Optimum Base Station

In this section, the mechanism of relative positioning is briefly introduced along with the sorting mechanism to determine the optimum base station.

As shown in Fig. 1, the code pseudorange ρ_b and phase pseudorange ϕ_b at base station b to satellite s measured at epoch t_0 can be modeled by

$$\rho_b^s(t0)=\varrho_b^s(t0)+\Delta\varrho_b^s(t0)+\Delta\varrho^s(t0)+\Delta\varrho_b(t0) \quad (1)$$

$$\lambda^s\Phi_b^s(t_0)=\varrho_b^s(t_0)+\Delta\varrho_b^s(t_0)+\Delta\varrho^s(t_0)+\Delta\varrho_b(t_0)+\lambda^s N_b^s \quad (2)$$

Where ϱ_b^s (t_0), $\Delta\varrho_b^s$ (t_0), $\Delta\varrho^s$ (t_0) , $\Delta\varrho_b$ (t_0), N_b^s are the geometric range, orbital errors, satellite-dependent errors, receiver-dependents errors, and phase ambiguity, respectively [20]. Also λ^s is the wavelength, defined as $\lambda^s = c/f^s$, where c is the speed of light and f^s is the frequency of satellite carrier. In relative positioning, the code and phase correction of the base station for the same satellite at base epoch t_0 is calculated as

$$PRC^s(t_0) = \varrho_b^s(t_0 - R_b^s(t_0) \quad (3)$$

$$PRC^s(t_0)=\varrho_b^s(t_0)-\lambda^s\Phi_b^s(t_0) \quad (4)$$

Similarly, in the rover receiver 'r', the code pseudorange ρ_r, and phase pseudorange ϕ_r are calculated for the observation epoch t because the range and range rate correction (RRC) referring to the base epoch t_0 are transmitted to the rover receiver in real-time. At r, the pseudorange, carrier phase, and the pseudorange correction (PRC) for the observation epoch t is modeled by

$$\rho_r^s(t) = \varrho_r^s(t) + \Delta\varrho_r^s(t) + \Delta\varrho^s(t) + \Delta\varrho_r(t) \quad (5)$$

$$\lambda^s\Phi_r^s(t) = \varrho_r^s(t) + \Delta\varrho_r^s(t) + \Delta\varrho^s(t) + \Delta\varrho_r(t) + \lambda^s N_r^s \quad (6)$$

$$PRC^s(t) = PRC^s(t_0) + RRC^s(t_0)\ (t - t_0) \quad (7)$$

where (t-t0) is defined as latency. After applying the predicated pseudorange correction $PRC^s(t)$ to the measured pseudorange of the rover receiver, the satellite-dependent bias has canceled out. Also, the base and the rover receiver have highly correlated satellite-receiver-specific biases in a short baseline area. Neglecting these biases, the corrected code and the phase pseudorange are calculated in the rover receiver as

$$\lambda^s\Phi_r^s(t)_{corr} = \varrho_r^s(t) + \Delta\varrho_{br}^s(t) + \lambda^s N_{br}^s \quad (8)$$

$$\rho_r^s(t)_{corr} = \rho_r^s(t) + PRC^s(t) \quad (9)$$

Where $\Delta\varrho_{br}^s(t) = \Delta\varrho_r(t) - \Delta\varrho_b(t)$ and $N_{br}^s = N_r^s - N_b^s$ are the difference of phase ambiguities [20]. To determine the coordinate of an unknown point concerning a known point. Thus, the baseline vector between the base and the rover is calculated with corresponding position vectors X_b, and X_r formulated as

$$X_r = X_b + X_{br} \quad (10)$$

$$V_{br} = \begin{bmatrix} X_r - X_b \\ Y_r - Y_b \\ Z_r - Z_b \end{bmatrix} = \begin{bmatrix} \Delta X_{br} \\ \Delta Y_{br} \\ \Delta Z_{br} \end{bmatrix} \quad (11)$$

Here, the base point coordinates must be accurately known to calculate the rover receiver coordinate with high precision. In the case of a kinematic rover receiver, it is continuously moving from one place to another. Therefore, the positioning information of the rover receiver is updated in the control unit regularly. Then, the distance between the rover and each base station is calculated and list out all neighboring base stations. The least distance is in the highest priority order. The distance between the rover and all neighbor base stations is calculated as follows

$$\Delta D_{rb} = E \cdot \arccos[(\sin(lat_r) \cdot \sin(lat_b)) + \cos(lat_r) \cdot \cos(lat_b) \cdot \cos(long_b - long_r)] \quad (12)$$

Where lat_r, lat_b, $long_r$, $long_b$ are latitude of a rover, latitude of a base, longitude of a rover, and longitude of a base, respectively. All values in radians. E is the equatorial radius of earth and ΔD_{rb} is the distance between the rover and a base station.

Furthermore, the availability of the base station is also measured through sensors data. For instance, ultrasonic sensors, voltage sensors, and 3-axis accelerometer sensors are used in this research. Besides these sensors, the other sensors can be used based on geographical and environmental conditions. The threshold values need to be entered at the starting time. In this rule of the assignment process, there are the following three cases.

Case I: $S_i \geq S_{TH}$ and $D_i \leq D_{i+1}$; optimum base station

Where S_i is the output of a cumulative function of sensors values, the threshold value of S_{TH} is needed to set after various experiments. Also, D_i is the least distance between the rover, for i^{th} base station. Similarly, D_{i+1} is the distance between the next adjacent base station and rover. In the above scenarios, if the base station satisfies case I, this base station is considered as an optimum base station and assign this base station till the subsequent handover is needed.

Case II: $S_i < S_{TH}$ and $D_i > D_{i+1}$; keep and hold (OK)

If the base station satisfies case II, the base station is considered as an acceptable base station or the next potential base station. Thus, these base stations are kept and hold for the next handover. Handover may require while the rover moved far from the earlier base station and approaches the adjacent base station. In this case, the earlier base station will be dropped off, and the adjacent base station will be handover for the operating base station.

Case III: $S_i < S_{TH}$; remove from the list (NG)

If the base station satisfies case III, it is considered functionless or not a referenceable base station. Therefore, this base station is removed from the list until it satisfies cases I or II. This situation may arise due to various reasons such as due to the accumulation of snow, increase of distance between rover and base station etc.

5.4 Base Station Assignment Process

After successfully determining the optimum base station through sensors' value and distance measurement, the handover mechanism is processed. We need to make configurations for this process such that the correction data and base station coordinate are streamed in both RTK engines.

In the RTK system, the base station sends corrections to the rover via a communication link. This correction signal enables the rover receiver to compute its position relative to the base with high accuracy. Radio Technical Commission for Maritime (RTCM) is the standard format with a binary data protocol for communication. The output stream should be changed in RTCM format to send standard messages and the real base antenna reference point (ARP). Therefore, a resident type application, str2str of RTKLIB [21], is used to input and output stream path. The input command seems as

```
./str2str-intcpsvr://localhost:60021#ubx
-out tcpcli://localhost:52081#rtcm3 -s 0
msg 1005,1077,1087,1097, 1127 -p
34.726598357 137.718089538 97.398
```

The data from the TCP server in the u-blox format (i.e., the message format type received by the u-blox receivers and fully configurable with UBX protocol configuration messages) as input stream outputs in the RTCM3 format.

Besides that, the coordinate of the base station (i.e., latitude, longitude, and height of the base station) and RTCM messages are streamed. These multiple signal messages (MSM), as shown in Table 1, are streamed as soon as they are configured for the corresponding GNSS.

In this approach, the base station's coordinates are changed when the base station is assigned dynamically. As every base station consists of a cellular SIM (subscriber identification module), the unique IMSI (International Mobile Subscriber Identity) number is used for the identification of each base station. Here, the base station is assigned as follows:

```
Chdist[RTK-engine number][base station's
IMSI number]
```

where `chdist` is a command to query the status of a package of a base station to the designated RTK engine; thus, the RTK engine at the rover side receives the observation data from that assigned base station, and finally assigned to the application layer for precise positioning.

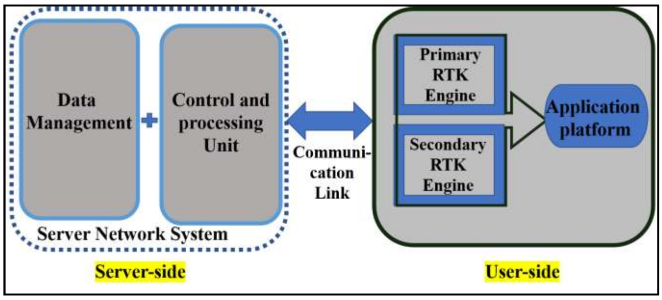

Figure 9: RuBBSA approach

5.5 Base Station Handover Mechanism

This section explains the principle of the RuBBSA algorithm and its approach for seamless handover. There are server backend and user end, as shown in Fig. 9. The server-side server network consists of two primary units: the data management and a control unit. The data management unit is designed to manipulate and manage data. Generally, all physical sensors data, all base stations coordinate data, and real-time differential correction data of corresponding base stations are collected and then manipulated. These data are processed to the central unit called as control and processing unit, where the rule is created to specify the most favorable base station from multiple base stations.

The RTK processing engine is placed on the user side, where the processing of differential correction signals from the base station and positioning observation from the rover receiver is carried. In this proposed system, two RTK engines named primary and secondary RTK engines are used to make a seamless handover operation. The primary RTK engine operates as a default RTK engine that runs until the handover is needed. The assigned base station from a control panel is linked with the primary RTK engine to provide precise positioning in the application layer. The final target of this research is to make a complete autonomous handover system; however, in this research, the server-based handover mechanism is proposed.

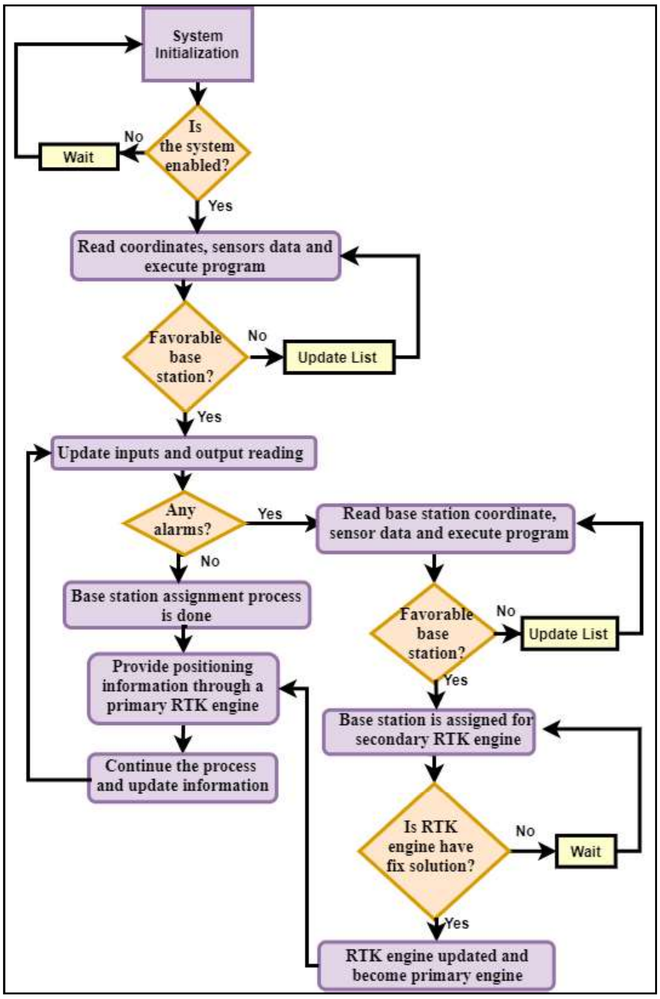

Figure 10: Flowchart of RuBBSA approach

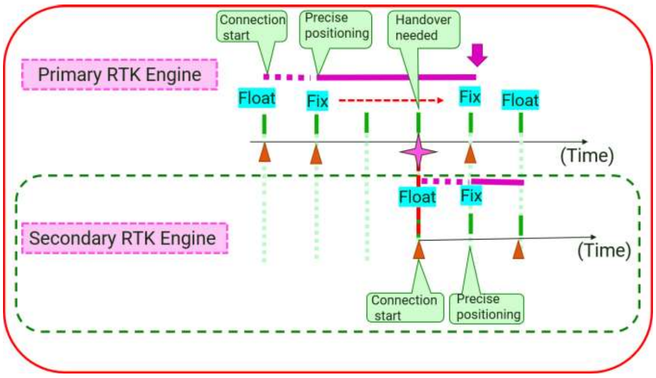

Figure 11: Seamless handover

The flowchart in Fig. 10 explains the mechanism of determining the optimum base station and seamless handover. In this handover mechanism, primary inputs are sensors data (i.e., ultrasonic sensor, accelerometer sensor, and voltage sensor) and coordinates of receivers (i.e., a base and a rover coordinate). From these inputs data, the base station availability has checked using the threshold value. Suppose the base station is a favorable base station based on the input values. In that case, it is considered the optimum base station (also called a favorable base station) and assigned that base station in the primary RTK engine. Here, we introduced an alarm function to check input values continuously. The alarm function is not activated until the currently assigned base station is fulfilling the condition to be optimum.

On the other hand, if the base station is out of the baseline area or the sensor's value is less than the threshold value, the alarm is created, which processes the handover. Thus, the currently assigned base station is replaced by the next adjacent base station through a secondary RTK engine. At that time, a new base station is assigned to the secondary RTK engine because the first base station is still operating in the primary RTK engine. In secondary RTK, the positioning solution is the float for a few seconds; therefore, removing the base station at the primary RTK engine is done after getting the fixed solution in secondary RTK. The removing process is done as

```
rmdist[RTK-engine number][base station's
IMSI number]
```

where `rmdist` is a command to detach the communication link between the designated base station and RTK engine; after that, the positioning solution is handled from the secondary RTK engine.

Table 1: RTCM message type and description

Message Type	Description
RTCM 1005	Stationary RTK reference station ARP
RTCM 1077	GPS MSM7
RTCM 1087	GLONASS MSM7
RTCM 1097	Galileo MSM7
RTCM 1127	BeiDou MSM7
RTCM 1230	GLONASS code-phase biases

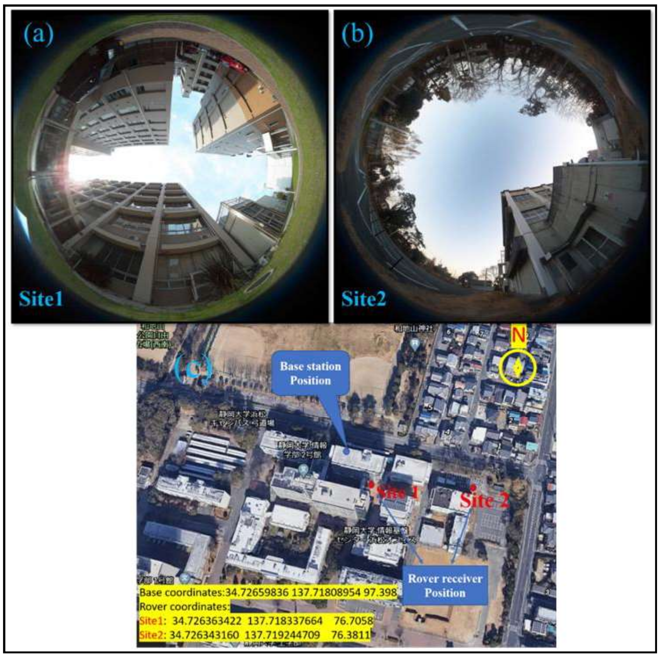

Figure 12: Rover Site location: (a) Site 1, (b) Site 2, (c) Google map

Thus, the positioning solution at the rover receiver is calculated without any interrupted or dropped signal, as shown in Fig. 11. These handover algorithms are written in the C programming language.

5.6 Multipath Detection Using Kernel SVM

The satellite signal consists of both direct and multipath signals. Therefore, the proper classifier is needed to mitigate multipath signals. This research proposed a multipath detection technique by using the classifier method. We have acknowledged that many researchers proposed a multipath signal detection method with different algorithms. They proposed a method such as detecting NLOS using observation data and existing 3D building data [14]. However, the process of detection is complicated and lengthy. Some researchers also proposed multipath detection methods using additional sensors [22]; however, those methods are complicated in differential positioning techniques in the practical field. Therefore, we proposed a practically implementable classifier without adding any additional sensors or hardware devices.

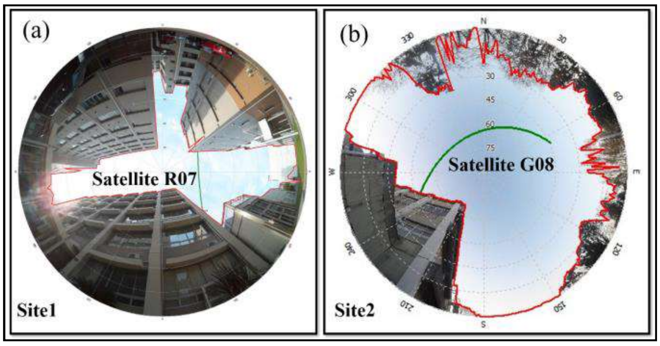

Figure 13: Mask Making; (a) Site 1, (b) Site 2

Figure 14: Graphical view of sensors data on webpage

In order to classify multipath and direct signals, we proposed a method that utilizes a classifier based on a machine learning algorithm. We used machine learning algorithms that can deal with linearly separable and non-separable data, called the kernel-based support vector machine (SVM). The reason behind this classifier is that the satellite signal may not always be linear. Thus, the data might not classify with a simple linear method to discriminate correctly.

Therefore, we need an algorithm that can deal with higher dimensions to make inseparable to separable form. So, we used kernel SVM in this work.

The kernel SVM is a supervised machine learning algorithm mainly used for classification purposes because it tries to learn similarities between datasets, and those become support vectors. Those support vectors are the data points that define the position and the margin of the hyperplane. The optimum hyperplane is the one that maximizes the margin, under the constraint that each data point must lie on the right side of the margin. Thus, only the support vectors are enough to make a classification. Here, multiple features data are used while training the classifier. The details of the multipath detection using kernel SVM, and features data are as follows.

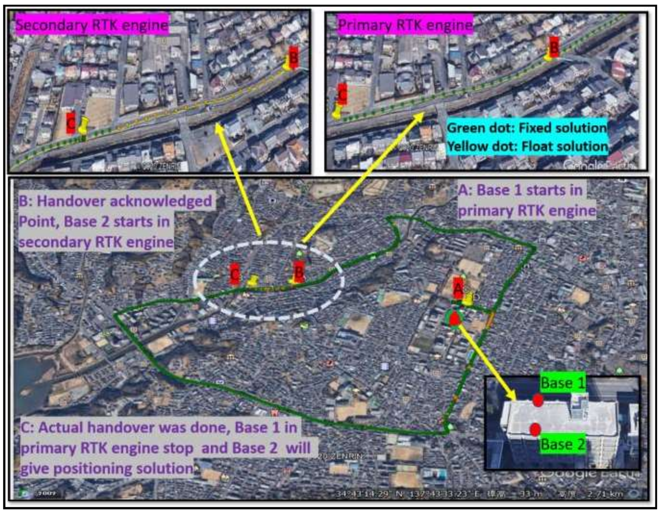

Figure 15: Experimental scenario for handover process

5.6.1 Differentiate CNR

We used signal strength as one of the major features data. In GNSS signal, correlations are essential for receivers to synchronize with the incoming signal, generate GNSS observables data, and retrieve the navigation message. Therefore, satellite signal strength is related to the magnitude of the correlation peak. In general, the signal strength of the direct signals is stronger than that of the reflected or diffracted signals. Even in a single GNSS, the signal strength called Signal to Noise Ratio (SNR) is widely used to exclude the multipath signals. Similarly, the signal strength called Carrier to Noise Ratio (CNR) is used in the RTK system. However, only considering the CNR value of the rover receiver is not practical because in some cases, when the satellites are very close to the mask line, we could not differentiate easily through fisheye image only. At that moment, the signal strength of the NLOS signal may higher than the LOS signal due to random errors. Therefore, we used the signal strength difference between the base and the rover receiver to correct those signals. Here, differentiate CNR is calculated by subtracting rover receiver's CNR with base station's CNR.

5.6.2 Elevation Angle

The signal strength is also dependent on the satellite elevation angle. The elevation angle of the antenna of a ground receiver has a peak value when the satellite is just above it and gradually decreasing. After some time, it reaches an elevation angle of zero. In the GNSS signal, as the elevation angle increases, the received signal strength keeps increasing. The signal strength is maximum when the satellite is just above the antenna. Previous researchers, Sheng-Yi Li et al., derived the analytic and mathematical relation between elevation angle and signal strength in their research work [23]. Therefore, we used elevation angle as one of the crucial features.

5.6.3 LOS and NLOS State

We also need to know the LOS and NLOS signals to train our machine learning model with these features' matrix. Therefore, a Fisheye camera is used to take a fisheye view image, which has finally used to determine the satellite LOS and NLOS state. Here, to find a distinct state between LOS and NLOS signals, the following procedures are processed.

A. GNSS data collection

First of all, we need to collect data from the base and the rover receiver. Here, A rover receiver is placed in the multipath environment to receive both direct and multipath signals. A base station is placed in an open sky area, such as the base rover, for direct signals only.

B. Analysis of Fish-eye View Images

After the data collection process, we need to distinguish the signal state, 0 for NLOS and 1 for LOS signal, of the rover receiver to use as a training data set. Therefore, the fisheye camera is used to capture the sky view from the rover receiver. Fisheye image and position of rover station are shown in Fig. 12. To estimate satellites' orientation (both NLOS and LOS satellites), we need to make a mask that differentiates an obstacle in a fisheye image. Thus, we need to adjust the azimuth of an image with an antenna by using an open-source platform called RTKLIB [21]. After that, the process of masking is carried out with the corrected binarized image, as shown in Fig. 13. The red line is a mask line that differentiates the obstacle's clear sky view and presence. In our case, obstacles are buildings and trees.

C. Extraction of NLOS features and Labeling

After that, the position of the satellite is estimated. The satellites found in a clear sky area are considered LOS satellites and marked as LOS signals. Similarly, the satellites which are found other than clear sky area are considered NLOS satellites.

Furthermore, the receiver's signal strength is varied by the satellite elevation angle due to differences in path loss and the antenna gain patterns. Therefore, the elevation angle is used as the next feature value while training the classifier.

5.6.4 Outline of Kernel-SVM

In the machine learning process, the data labeling process is essential to improve accuracy and efficiency. The main challenge is to decide which features data are more responsible and make the overall performance of a predictive model. Our model uses the matrix of features, i.e., elevation angle and differentiate CNR value, with dependent variable vector, i.e., the NLOS and LOS state by the fisheye image as a features data. Here, LOS and NLOS states are predefined target attributes used for training the algorithm that we will predict satellite states from future satellite data. We mainly focused on features data, training data ratio, and kernel tricks to make the correct label for learning data. First, we chose responsible features data, then we classified train and test set data in maximum performance ratio, i.e., 80% of our data are used for the training process, and the rest are for the test process. Finally, we trailed with different algorithms such as decision tree, naïve Bayes, K-nearest etc., algorithm; however, we found the best result in the Gaussian radial basis function (RBF) kernel trick technique. SVM uses a Gaussian radial basis function (RBF) kernel trick technique to transform the input data in this classifier approach.

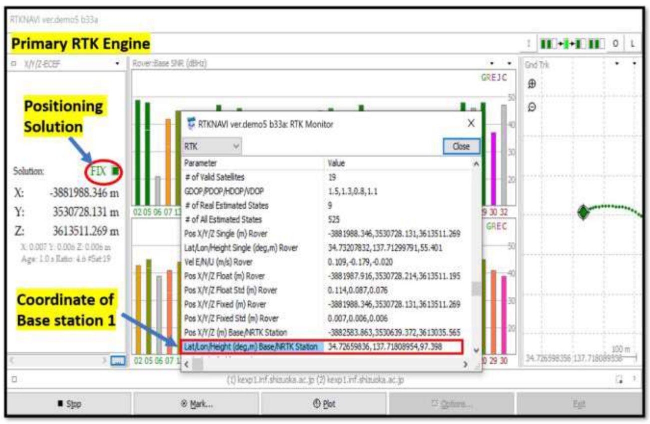

Figure 16: Result in primary RTK engine

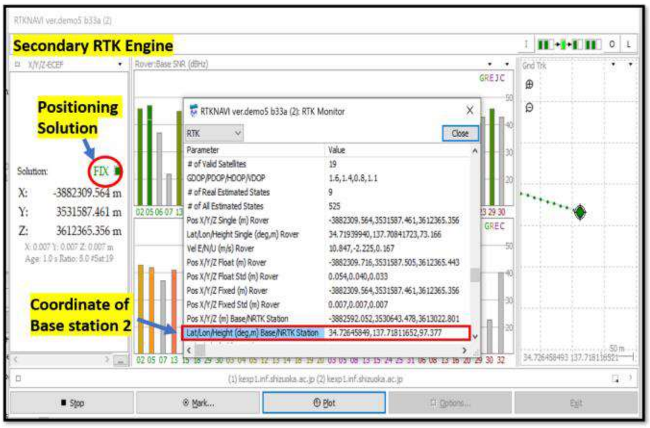

Figure 17: Results in secondary RTK engine

As a result, the optimal bounds of the target classes are obtained to classify nonlinear data, which we consider the right label for our system. Also, feature scaling is used to standardize datasets. The detailed working environments and results are described in the next section.

6 RESULTS AND DISCUSSIONS

To test the proposed system's performance, the base station was set up and tested in the practical field. A set of task actions and obtaining results are described in the following sub-section.

6.1 Discussion of Monitoring System and Its Performance

Base stations are equipped with digital sensor network systems that were deployed throughout all base stations. We have considered three significant problems in the mountain and snowy regions that affect the base station conditions. These problems are (1) snow accumulation, (2) natural disasters, and (3) power outage problems. Various cost-effective and easily applicable sensors are used to address these problems concretely. To check the monitoring system's performance, we have done our experiment in the dense snowy placed named Wakkanai, Hokkaido, where there was heavy snowfall, dense fog, and cold weather. We have done that experiment to check the performance of the prototype on the snowy area that consists of multiple sensors with a cellular RTK receiver. The main goals of this experiment are (1) remotely monitor the base stations' conditions (such as snow level on antenna, antenna's orientation, power supply status, etc.) in real-time, (2) send the satellite signal of the base receiver to the server system using a cellular network.

In our system, the microcontroller works with a sketch file that creates a data feed from the ultrasonic sensor, accelerometer sensor, and voltage sensor. Here, an ultrasonic sensor provides snow height levels. Similarly, the accelerometer uses for detecting the orientation, gesture, and motion of the antenna. Those are the ground data that we used to monitor the base station. Similarly, the GNSS receiver, which is supposed to work as a base station, is embedded with a cellular LTE model to send the satellite signal to the server using a cellular network. Those sensors' data are sent to web-based applications and displays on a web page correctly.

These data are received as byte-type data. Therefore, byte type data is decoded in Harvest's GUI and displayed as a column of primarily processed data. These data can be saved to the local file or own server system. Finally, those data are displayed in graphical form were shown in Fig. 14. Also, the sensors' data are used to detect the healthy or unhealthy state of the base station.

As a result, the optimum base station could be assigned to a rover receiver. From this experiment, we checked hardware and software performance regarding sensors-based base stations. We concluded some bits of knowledge such as sensors accuracy and its real-time performance.

First of all, our monitoring system in the snowy region is perfectly worked. We were able to collect data and monitor it in real-time through the sensors. Secondly, the wireless data collection using the cellular network to server system is smoothly done for both cases, sensors and GNSS signal.

6.2 Discussion of Seamless Handover and Its Performance

In order to make a robust RTK infrastructure, we need to address the networking mechanism of the base station. Therefore, we proposed a seamless handover mechanism between two or more base stations in network cellular RTK. After the monitoring system, proposed algorithm, its practical use, and performance evaluation were done with static and kinematic rover receivers, as shown in Fig. 15.

We tested the handover process, system's functionality, and performance concerning the RTK accuracy. To test the performance of the proposed algorithm, we have done our field test experiment in Hamamatsu, Japan, where the surrounding environment contains tall buildings and dense traffic. In our experimental kinematic scenario, two static base stations and one kinematic rover receiver are used. For this experiment, the base station assignment process was computed manually through a server system.

At first, we have connected all base stations in the control server system where available base stations are displayed with their unique identity. As every base station consists of a cellular module as an internet provider, the unique IMSI (International Mobile Subscriber Identity) number is used for base station identity. Basically, a base station is assigned to the primary RTK engine.

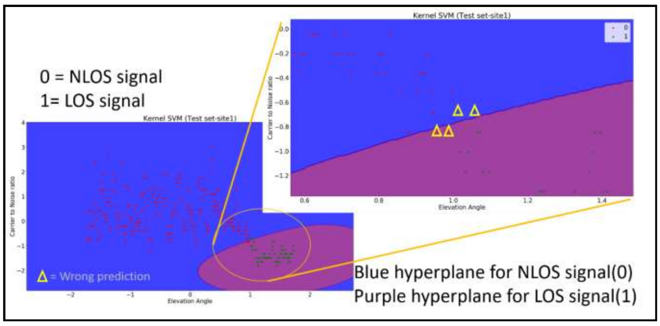

Figure 18: Experimental results of site 1

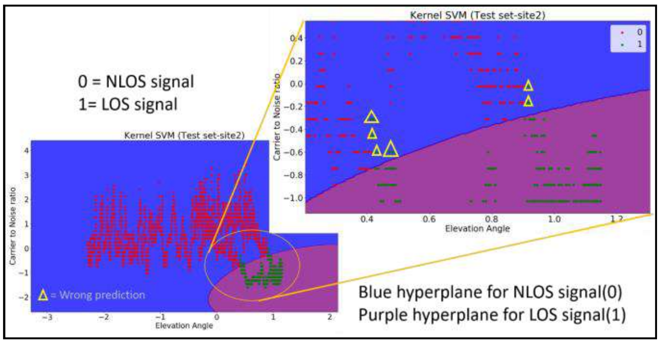

Figure 19: Experimental results of site 2

This selected base station started a connection to the rover receiver and got a fixed solution after a few seconds, as shown in Fig. 16. After getting a fixed solution in the RTK engine, the positioning information is ready to use by applications. At the time of handover, the new base station is assigned through the server system to the user end. The communication link is established to the secondary RTK engine because the first base station is still operating in the primary end.

In this case, the secondary RTK engine receives correctional information from a base station and provides the fixed solution, as shown in Fig. 17. After getting a fixed solution in the secondary RTK engine, the primarily selected RTK engine went to ideal mode. The secondary RTK engine starts its positioning solution and becomes the default RTK engine. An open-source program package of RTKLIB library with a program package is used as RTK engines.

In our experiment, we used two base stations at a fixed location and near each other. However, those two base stations might not be consistent; thus, the precise positioning solution could be different in the primary RTK engine and the secondary one. Therefore, to make a seamless handover on that condition, we need to calculate the positioning error in both RTK-engine, such that at a point, the positioning error is conceding and become minimum; thus, handover could be done continuously. For instance, if we plot the positioning solution of the primary RTK-engine with the positioning solution of the secondary RTK-engine, the difference in positioning solution can be calculated and vice versa.

Table 2: Processing components

Name	Description
Features' data	Differential CNR, elevation angle, azimuth angle, distinct state of NLOS(0) and LOS(1)
Programming language	Python (V. 3.7.7)
Libraries	NumPy (v. 1.16.4), Matplotlib (v. 3.1.0), and Pandas (v. 0.24.2)
Test set value	0.20
kernel	Radial basis function (RBF)
Computer environment	Windows 10, 16GB RAM, i7-8550

From this experiment and result analysis, we concluded that the seamless handover is possible with two RTK engines in a simply smart way. If we combine both the monitoring and seamless handover mechanism, this development may upgrade the performance of network RTK to a new level.

6.3 Multipath Detection and Its Performance

The classification results of the kernel SVM-based classifier are shown in Fig. 18 and Fig. 19. We have chosen those satellites for both experiment areas, which had changed their position from being LOS to NLOS or vice versa. Observation data from the rover receiver and base receiver is converted into an excel file to prepare a dataset for training. Data and time, satellite number, azimuth, elevation angle, differential CNR and the distinction state for LOS and NLOS signal are used as the training dataset. Here, the distinction set is marked 0 for NLOS and 1 for the LOS satellite. The processing components are shown in Table 2. To split the dataset into the train and test set, we used a test set value of 0.20 (i.e., 80% sample data are used for the training set, and 20% existing data is set for the test set).

After that, feature scaling is applied to normalize the features data (i.e., independent variable) with a particular range and also helps in speeding up the calculations in an algorithm. After that, we applied the kernel SVM model is created and applied to the training data set. The experimental results in Site 1 and Site 2 are described in the following section.

A. Experimental results in Site 1

After sufficiently train our kernel SVM model, the test experiment is done for an hour of data (excluding observation data for the same elevation angle). The result of the classifier is shown in Fig. 18. To analyze the result, we used a graphical view and confusion Metrix. We found that 98% of NLOS data and 90% of LOS signals are predicted correctly.

B. Experimental results in Site 2

Similarly, the experiment is carried out on Site 2. For this experiment, three hours of data are used to train the model. The experimental result is quite improved while using all experiment data (i.e., every CNR value is used regardless of the same elevation angle) shown in Fig. 19. After analyzing the results through the confusion matrix, we found that 99% NLOS and 97% LOS signals are predicted correctly. Also, multiple experiments were conducted to analyze the accuracy of the prediction. On average, 98% NLOS and 95% LOS signals are predicted accurately.

7 CONCLUSION

This research has presented the novel perspective to build a reliable RTK infrastructure that is applicable in snowy/mountain and urban areas. We proposed three new components into the system to address the issues of those areas, especially targeting the reliability and higher positioning accuracy for movable objects.

Firstly, we practically implemented a mechanism of detecting an unhealthy base station in order to monitor its availability. We have practically checked the performance of sensors embedded cellular RTK base station in Hokkaido, Japan. We used different sensors in the base site to monitor its status through the internet. Those data are used for web-based monitoring purposes, such that a base station's state (i.e., healthy, or unhealthy) is easily noticeable on the user side. Experimental results confirmed that the base station's availability is regularly ensured in real-time.

Secondly, we proposed an algorithm to assign the optimum base station from multiple base stations in order to provide continuous and high accurate positioning for a portable rover receiver. The actual field experiment was done in a network RTK system to explore a seamless handover mechanism in Hamamatsu, Japan. The concept of assigning optimal base station is based on two factors: base-rover distance and sensors value. For the seamless handover, we proposed the usage of two RTK engines on the user side, such that the positioning accuracy was maintained at centimeter-level before and after handover.

Thirdly, the multipath detection model is proposed as a final component of our robust infrastructure. A new method of distinguishing the LOS and the NLOS multipath signals was developed to improve RTK-GNSS positioning accuracy in urban environments. A classifier based on the kernel SVM technique is proposed using receiver signal strength and its elevation angle. As a result, around 98% of the NLOS multipath signals and 95% of the LOS signals were correctly classified. From the experimental results, we have confirmed that the proposed technique can effectively predict future CNR and helps to mitigate multipath signals.

By combining these three components' results, we have confirmed that our approaches significantly impact building a robust RTK-GNSS infrastructure for continuous and precise positioning. Also, we have verified that continuous correctional signals and precise positioning in challenging environments can be achieved from our method for a movable object.

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