Verification of Personal Location Data Consistency for COVID-19 Dissemination Prevention Cancellation

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Abstract: Recently, several disasters have occurred. In particular, COVID-19 has had the strongest impact of many disasters in recent years. However, the world is also overcoming COVID-19 in line with the era of the Fourth Industrial Revolution. In preparation for these COVID-19 events, this paper aims to use the Moving Query Object to increase CPU performance for these tracking systems by tracking smartphones worldwide, using LBS systems, such as Wi-Fi, 5G, GPS, etc. So we have created an artificial intelligence-based COVID-19 Location-Based Research Model and have presented the Artificial Neural Network Positioning Research Model Design. Based on the model presented, the Architectural Neural Network Positioning COVID-19 Location Forecast Architecture was also designed. We also want to see real-time information from people infected with COVID-19 for smart cities. Finally, these tracing systems were simulated and tested 10 times and 1,000 times for comparative analysis. Therefore, active tracking and performance are studied when COVID-19 viruses and other disasters occur in smart cities in the future.

Keywords: COVID-19; COVID-19 Monitoring; Positioning Station Algorithm; Intelligent Agent; Artificial Intelligence; Smart City.

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1. INTRODUCTION

In recent years, society has had several chaotic relationships with new viruses, such as SARS and coronavirus. With the worldwide spread of these viruses, the global economy, education, culture, manufacturing, and high technology are all coming to a standstill. Also, the existing SARS-CoV-2 or MERS contained deadly viruses, but vaccines existed. So, we are stopping the spread of the virus in a short time. However, in the case of COVID-19, there are not any vaccines yet, and through social infection, the virus is spreading at greater risk.

As a result, the whole world is experiencing a lot of turmoil, reaching the levels of the oil shock and the global economic crisis of 2018. In addition, the current COVID-19 virus is affecting several industries. The coronavirus also belongs to one large group of viruses. Coronavirus is a virus that usually infects animals, but it has become a rare strain and is thickened by a person who infects humans.

A new type of coronavirus, now called SARS-CoV-2, causes an infection known as COVID-19. When a person is infected with a coronavirus, severe respiratory problems usually occur as minor symptoms, similar to those of a cold. Among them, viruses such as SARS and MERS (Middle East Respiratory Syndrome) cause fatal diseases, such as pneumonia. So, the reality is that the world is almost paralyzed and tens of thousands of people are killed.

In this paper, we use the infrastructure of LBS and 5G networks for prevention and active response to virus outbreaks, as well as artificial intelligence and big data analysis to track the location information between individuals in order to prevent the spread of the virus, and

to send accurate information that fits each individual's location without error. This allows us to classify data, verify data, and identify data. We need to be researching the required M-LBS matching framework and using the necessary disaster network, real-time monitoring of individuals' health and obtaining alerts and actual data around the time of outbreaks of the virus, securing verification information, and dividing several types of architecture and SON (Self Organized Network). It is necessary to study the automatic healing and automatic verification of the concept, and the network system that is automatically recovered.

In addition, this study shares location information between these individuals while encrypting all of this data. Therefore, the architecture was designed without personal information protection, and it exposes information. This study started with the idea of how disasters can happen and how to overcome them.

So, we will try to expand this research a little bit. Chapter 1 gives an overview of this paper. Chapter 2 is the stage of analyzing the existing research, learning about the concept and data analysis techniques of viruses, big data analysis techniques and deep learning analyzers, and M-LBS, a location-based service, with this data. Chapter 3 designs the framework and architecture for accurate contact information and analysis of whether this user is actually infected with the virus to communicate with individuals, which are the key technologies of this paper. Chapter 4 concludes with future research directions and conclusions in preparation for future outbreaks of various viruses **Fig. 1**.

Fig. 1. Concept of Individual Location Data Consistency Verification to Prevent COVID-19

2. RELATED RESEARCH

2.1. COVID-19

Recently, a variety of situations have been changed by the COVID-19 virus. This is because it is affecting all industries, including the world economy, culture, education, and the manufacturing industry. COVID-19 is an acute respiratory disease caused by the SARS-CoV-2 virus. SARS-CoV-2 is a variant of the coronavirus family, which included the SARS outbreak in 2003 and the MERS outbreak in 2015. It was first reported on December 12, 2019, and according to this report, the first patient was found in Wuhan, Hubei Province, China on December 1, 2019 [1].

However, the cause of the initial outbreak and the route of transmission of the virus are still unclear. From January 2020, it began to spread around the world, including all continents, except Antarctica and some countries and islands, and it recorded a high number of infections and deaths. The WHO (World Health Organization) declared an international public health emergency on January 31, 2020, upgraded the global risk level of COVID-19 to 'Very high,' as of February 28, and finally declared it a pandemic on March 11, 2020. Information related to each country's situation and response can be found in the transitional documents, in the country-specific response documents, and in the response documents of each community.

If you want to quickly find more information about Korea's confirmed patients, refer to the coronavirus infection-19/ status.

Republic of Korea (ROK), and the coronavirus infection/response/Asia/Korea if you want to check the response status of the Republic of Korea. In the early stages of the outbreak, the term "pneumonia," which was temporarily used by the WHO as a symptom of Buddha's lung disease, began to be used in countries, such as Korea, China, and Japan. However, the disease was referred to as a new type coronavirus infection, which translated to the "Novel Coronavirus." In Japan, the name of the new coronavirus is also used in combination with the name of the new coronavirus. In North Korea, it has been named "the new coronavirus".

The WHO in Geneva confirmed the official name of the infection as COVID-19 (Coronavirus disease 2019) [2]. "CO" refers to "Corona," "VI" stands for virus, "D" stands for disease and "19." In Republic of Korea (South Korea), people say 'coronavirus infection-19'. There is also a name for the virus that caused it. The International Committee on Taxonomy of Virus (ICTV) identified it as a variant of

SARS-CoV, and thus named it as so. In response, China is protesting and proposing to change the name to CARS-CoV and so on, but countries actually do. WHO Director-General, Thedros Adhanm Grubber Jesus also calls the cause virus COVID-19. In addition, the transmission path of the coronavirus in humans is similar to other respiratory infections (e.g., influenza), and the most common infection pathways are:

- Vapor that is excreted when coughing or sneezing.
- Close contact, including care for the infected.
- Touching an object or surface that contains the virus, or touching the eyes, nose, or mouth without washing hands.

Every day we learn how easily this new virus spreads and how long it takes for a person to develop symptoms after becoming infected. In addition, there are no studies showing that people of a certain race or nationality are more likely to be infected with COVID-19, but people of all races and nationalities have been infected with the new virus. Fig. 2 shows COVID-19 Infection Status.

Fig. 2. COVID-19 Infection Status Source: WHO (World Health Organization)

2.2. LBS (Location Based System)

Recently, as mobile phones have become increasingly popular and each person in a household has their own device, personalized location-based services have also developed. These service providers can measure an individual's location through GPS chips built into wireless terminals. In this case, the wireless terminal is directly responsible for the entire function of receiving signals from multiple GPS satellites, calculating location coordinates based on these signals, and looking up a variety of information through the mobile network [3-6].

In addition, depending on the type of mobile network operator and location information service, the location is found through a single base station and is used without using

a method of calculating location relationships between multiple base stations and terminals. Since the mobile network is always carrying out terminal mobility management based on the characteristics of the base station, this method can be used to provide location-based services without the addition of a separate measurement system and the load of measurement calculation at the request of location is minimized [7-10].

However, depending on the current mobile network, terminals that have individual cell phones have difficulties in directly performing satellite signal reception and in coordinating calculation functions, due to low power and low computing performance. Thus, a variety of mixed measures have been devised to use GPS signals as an aid in calculating location coordinates in combination with adding distance relationship and propagation status measurements at adjacent mobile communication base stations [11-15], which are commonly referred to as A-GPS(Assisted GPS) [16-19].

At this time, both the radiolocation method and trilateration method are used to calculate the location relationship based on the propagation state between the nearest base stations and terminals. The accuracy of the location measurements is the lowest since the GPS and corresponding satellite-based positioning methods are the highest, and the base station methods can only measure regional distinctions, rather than latitudinal coordinates. One of these methods does not necessarily enable the implementation of location-based services. Due to the fact that current mobile networks are equipped with a variety of terminals with different location-level performances, ordinary mobile carriers offer location-based services using a mix of GPS, A-GPS, and base station methods [20-21].

On the other hand, the trend of identifying the location of users or objects in areas other than mobile networks, then reflecting them in services, continues to increase. Due to new specifications of mobile network environments, such as mobile networks using wireless LANs, or Wibro, as well as those in wired Internet environments, research and industrialization of IP address-based user location recognition technologies are under way, and it makes sense to include them in the comprehensive measurement technology for location-based services.

However, a variety of positioning technologies are available in the world, specifically, indoor localization. GPS and indoor GSM do not work very well, therefore, they can be used like other technologies, such as Bluetooth, ultra-wideband, RFID, and Wi-Fi. However, this technology has

a problem of providing the best solution for a particular LBS problem [22-24].

The location-processing platform has location-based service components that function to aggregate and process the locations of users or objects, which is obtained by the measurement technology and transforms it into consistent representational information and serves or stores components of the location application group, through an interface with the network.

In addition, the GSM, CDMA-based mobile network model defines a GMLC (Gateway Mobile Location Center) as a facility that serves as a gateway to request base station routing information for terminals and as a method to support linkage with location applications that are present in IP networks, in conjunction with mobility management systems within the mobile network. These GMLCs can be classified as a location-handling platform. In addition, the MPC (Mobile Positioning Center) that is assigned to play a similar role in the A-GPS mobile location-based service configuration is an example of a location-processing platform and is managed by the OMA (Open Mobile Alliance) for standard protocols with location applications in order to access the location integration capabilities of the GMLC/MPC [25].

In this non-mobile network environment, facilities and services that serve to aggregate the location of users and objects, and to integrate protocols with a group of location applications, can be classified as a comprehensive location-handling platform. Research and public standardization of these platforms is needed in line with the convergence flow of wired and wireless network services.

It is a service that can communicate with a location processing platform to provide dynamically processed content, based on the location of individual users and objects, or that can manage the collected location information. It is also layered into a Location Application Server and LBS (Location Content Server) in the mobile network, which is also nicknamed the 'LBS platform' and is a facility that simultaneously serves as a basic location-based add-on and gateway for external content services in [26] the mobile network. Fig. 3 shows COVID-19 Infection Status.

Fig. 3. COVID-19 Infection Status (Source: WHO (World Health Organization))

2.3. Tree-Architecture

The tree structure of the database is a recursive form of data structure in which multiple child nodes are connected under the parent node, then the child nodes are connected back to the other child nodes. However, if the child of a child node is connected to a parent, it is not usually accepted as part of the tree. A tree has some basic and interesting properties, such as the number of edges attached to a new node that are created when a node is pulled out of the tree structure [27].

If you continue to ride from your child's node to your parents' side, you end up with a single node without a parent, which is called a root node [28]. This tree structure is similar to the structure of an actual tree, hence the name. A tree with a defined root is called a rooted tree, and a tree without a root is called an unrooted tree. The loaded tree defines several terms.

The head defines the height of the root as zero, and the height of the child is 1 greater than the original node. The definition of a leaf node is a childless node [29]. In an unrooted tree, a node with a dimension of 1 defines the terminal node. The most popular type of tree is the binary tree, which is the simplest form of the tree, with up to two child nodes coming under the parent node. The two child nodes are usually separated into a left child and a right child, and can be implemented in a structure with one value and two pointers, which point to the left and right child nodes, respectively. In a tree structure that can typically have no children, a node can be added for each child in excess of one, in order to convert to a binary tree structure, which places the original child node to the left of the new node and the sibling node to the right (Left-Child, Right-Sibling). All

- Full Binary Tree: All trees have 0 or 2 children.
- Perfect Binary Tree: All leaf nodes are the same height.
- Complete Binary Tree: A binary tree with a left child, if all the leaf nodes have a maximum height difference of 1 and have a right child on all the nodes. In other words, the tree is filled with elements one by one, from the left to the right.

- Generally, a nonlinear, binary structure is implemented so that each node has a child's pointer. However, for a fully binary tree, it is also implemented using an array, which is filled from the left. Considering a sequence, starting with number 1, the left child of the n th element should be composed of $2n$ and the right child of the n th element should be composed of $2n+1$. In addition, the parent node of the n th element becomes the $\lfloor n/2 \rfloor$ element. Fig. 4 shows Tree-Architecture.

Fig. 4. Tree-Architecture

2.3.1. BST (Binary Search Tree)

Binary trees are the most commonly used form of trees. It is the simplest form of a tree, with up to two child nodes coming under the parent node. Two child nodes are usually separated into a left child and a right child [34], and can be implemented in a structure with one value and two pointers, which point to the left and right child nodes, respectively.

In a tree structure that typically has ‘n’ children, each child with more than one node can be added to convert it to a binary tree structure that places the original child node on the left of the new node and the sibling node on the right (Left-Child, Right-Sibling), which allows all trees to be reconstructed into the form of a binary tree [35] (even if the left and right are changed).

Therefore, unless there is a particular reason, a tree is usually implemented as a binary tree. The following are the types of binary trees: Generally, a nonlinear structure [36],

the binary is implemented so that each node has a child's pointer, but for a fully binary tree, it is also implemented using an array, which is filled from the left. Considering a sequence starting with number 1, the left child of the n th element should be composed of $2n$ and the right child of the n th element should be composed of $2n + 1$. In addition, the parent node of the n th element becomes the $\lfloor n/2 \rfloor$ element.

- In-order traversal: A tour method that visits in the order of the left offspring, yourself, then the right offspring. A median tour of the binary search tree can produce aligned results.
- Pre-order traversal: A tour method in the order of yourself, the left offspring, then the right offspring.
- Post-order traversal: A tour method in the order of the left offspring, the right offspring, then yourself.
- Level-order traversal (aka a Breadth-First traversal): A way of touring nodes in order of level.

The above three methods can be implemented using stacks, while level sequence can be implemented using queues.

2.3.2. B-tree (Red-Black Tree)

The Red-Black Tree, a type of B Tree, is a self-balanced binary navigation tree, and a tree with a color property attached to each node. In both the ideal and worst-case scenarios, all of discovery, insert, and delete are the ultimate trees with time complexity “O” ($\log N$). When expressing structure, attach a null to the end of a node that has no children, unlike other trees [37]. This null leaf node is only used to represent the end of the tree.

In addition, the following conditions require the tree of these databases to be satisfied:

- Every node is either red or black.
- Root nodes are black.
- All Null Leaf nodes are black.
- The red-node child is always black. Therefore, only the black nodes can be the parents of the red nodes.
- To put it plainly, black nodes can come out in succession, but red nodes cannot.
- All paths from any one node to the leaf node always have the same number of black nodes, except for the null leaf node.

The last condition is that if any node is set to the root node, the black-depth of the red black tree is always constant. In addition, the total depth is limited to a minimum of $1 \lg(B)$ to a maximum of $2 \lg(B)$, only if the number of black nodes is B , because the red nodes cannot always be followed by the previous condition, “The child nodes of the red nodes are always black”. So, when you define a Red-Black Tree,

you draw a red node, so it connects to the left and right without affecting the height [38].

In addition, insertions and deletions often require color conversion or tree rotation of the nodes, and implementation is quite complex, but they look very efficient in their use. Set, map of C++ STL was implemented using this red black tree. It is also very similar to the 2-3-4 tree, and an all Red-Black Tree has a 2-3-4 tree that responds one-for-one. The 2-3-4 tree contains between one and three data per node. Marking the data in the middle of the two in black and the data in red, the left and the right make it equal to the Red-Black Tree.

2.4. Deep Learning for Smart City

Deep Learning is called in-depth learning, as it uses an Artificial Neural Network with multiple layers. Therefore, deep learning is not a completely different concept from machine learning, but rather it is a type of machine learning. In traditional machine learning, a person had to analyze and judge for himself which of the various features of the data they wanted to learn. However, in deep learning, the machine automatically extracts and learns the characteristics from the data that it wants to learn. The biggest difference between deep learning and machine learning is whether a machine is self-learning or not. Therefore [39], deep learning can be defined as a technology in which a machine automatically learns important patterns and rules from large-scale data and makes decisions or predictions based on these findings. The most basic concept in deep learning is the Neural Network. Neural networks refer to the connective structure of neurons, one of the biological characteristics of the human brain [40].

The network structure that is modeled after these neural networks is called the Artificial Neural Network (ANN). There are about 100 billion neurons in the human brain, and one neuron only plays the simple role of receiving signals from another neuron, then transmitting these signals to a separate neuron. However, the human brain can think differently, based on the flow of signals made by these neurons, and it is the artificial neural network that has tried to implement this concept on a computer. An artificial neural network is a network of structures in which multiple neurons are interconnected and the input layer provides the data that you want to learn [41]. This input data is processed over several levels of a hidden layer, resulting in the final results being outputted through the output layer. These three or more overlapping neural networks are called Deep Neural Networks (DNN) and machine learning is specifically called

deep learning. Perceptron was the first algorithm to describe an artificial neural network theory designed by Frank Rosenblatt, an American psychologist, in 1957.

Frank Rosenblatt proposed the single layer perceptron concept, which consists of only the input and output layers, as the simplest perceptron [41].

Here's how the single layer perceptron works.

- The input and weight of each node should be multiplied by one another.

- The combined values should be compared to the threshold (which is the reference value for selection) that the activation function has.

- If the value is greater than the threshold, the neuron is activated. If it is less than the threshold, the neuron is disabled.

This figure illustrates the concept of deep learning and demonstrates the development of machine learning through a multi-layered level structure [42]. As shown in Fig. 5, deep learning is evolving through neuron computing, machine learning, etc.

Fig. 5. Deep Learning Architecture

3. COVID-19 LOCATION-BASED RESEARCH MODEL

3.1. Issue Raising

Based on the initial fatality rate resulting from the COVID-19 infection, compared to SARS-CoV and MERS-CoV, which have been major worldwide issues, this paper may seem less lethal to date. However, the WHO has declared a state of emergency as it continues to spread rapidly around the world through human-to-human transmission. In addition, there is still much to be revealed, such as the movement and activity of an infected person whose exact epidemiology and propagation paths have yet to be identified. Therefore, based on the experience of the

new coronavirus from humans, the current epidemiological studies to overcome the crisis, as well as efforts to develop a diagnosis, treatment, and medicine, continue. To this day, many doctors and nurses are still working hard to fight the virus. After all, the direction of research on how to respond and minimize damage after the virus has emerged as a way of a disaster system, rather than coping with every outbreak of these viruses. So, from a medical point of view, if the existing virus spread is stopped by making a vaccine and dealing with it, this study includes research on how to solve the problem in ICT oligopoly. There is a point in this study that future cloud-based telecommuting can minimize face-to-face contact in the context of a virus. However, there are real limitations in everyone working remotely.

That's why not all employees need to go to work, but a more fundamental approach is needed. This paper improves the weaknesses of virus-related Apple products that are currently available in case of a virus, so that users can access the M2M communication-based cloud to communicate between individuals and access the cloud on a more accurate carrier to view the location of individuals anytime, anywhere. However, the current communication method is that the range of errors and the information of others should be consistent in the view of each individual because of the personal communication with satellite communication, Wi-Fi, 5G communication, etc. In other words, we would like to study the technology of detecting, identifying, and notifying others if they were infected with the virus. The research will begin to overcome new viruses in the future by using an artificial intelligence system and a tree algorithm in a database.

3.2. Research Methodology

This study has recently caused chaos around the world, due to the COVID-19 virus. However, this worldwide viral infection is not only a problem right now. It has existed in the past and it will exist in the future. In addition, in case of such a disaster, we would like to discuss a methodology for accurately recognizing the location of COVID-19 virus infections, using location-based services, and applying them in real time to objects that can be tracked correctly using location-based services [42-44].

First of all, we can provide location-based services through satellite. These location-based systems have technical methodologies using 5G services and Wi-Fi indoors. However, objects that are infected with the virus are moving in real time. Data that has already left its place is important, but data on the real time location of an object

has become very important. Therefore, it is very important to distinguish accurate location data by reflecting it in real time [45-47].

Location Based Service (LBS) refers to a technology used in services that provides functions to users based on location information that is obtained through a network or GPS. That's why we use real-time location-based artificial intelligence algorithms to prevent viruses from infecting other individuals. This method, of course, is based on real-time processing. In addition, these viruses move in real time, and these pathways have blind spots.

That is, the infected are able to move continuously. When you move like this, you search for those who are infected around you, reflect it in real time, and verify the unnecessary data if you go out of the radius of your location. This study began because the existing location-based services make personalization platforms for the public interest and, based on the existing T-Tree location-based algorithms, A-GPS, Wi-Fi positioning systems (WPS), and location-based technologies (LDT) (mobile communication-based, GPS-based, hybrid-based, etc.) are not accurately detecting for viruses, and this propagation is aimed at the world.

In addition, by using the tree of the database and applying the actual artificial intelligence neuron algorithm to the positioning system [48-49], the error range is reduced by accurately detecting and applying the internal location data in real time. The verification of real-time location data, rather than batch processing, and the future deep learning algorithm of these verified data are combined. So far, location-based services have several problems, including the problem with location measurement and the inability to reflect this data in real time, and there are several technical problems with this service. However, future viruses are aimed at preventing the spread of these strains because there are many mutations. On top of that, the goal is to expand ICT technology, such as GPS, WIFI systems, Bluetooth, and systems to minimize the error range and safely prevent viruses by pushing real-time responses.

3.3. Artificial Neural Network Positioning Research Model Design

The Position Detection Technology (PDT) for the detection of the AI COVID-19 virus is a technology for measuring the location of mobile terminals, which uses a network-based (Network Based) method using base station reception signals in telecommunication networks, and a handset-mounted GPS receiver (Hands Based) method

using both a mixed and a hybrid method. This foundation is intended to minimize the shaded areas [50].

In addition, the network-based method does not use additional special devices on the terminal, but the location accuracy varies, depending on the cell size and measurement method of the base station of the network. The measurement error generally ranges from 500 meters to 1 kilometer. So, this paper uses a tree-based operation method to reduce measurement errors by utilizing the accuracy of a neuron algorithm that reduces these measurement errors.

It also uses a hardware-based handset infrastructure. However, such a method requires additional signal receivers, such as GPS receivers, to be installed on handsets, so there becomes a problem in which signal reception is interfered with in urban areas with a larger number of buildings, forest areas with a lot of trees, or indoors. However, it is a more accurate method than network-based methods.

To solve the problem of these two methods, the neuron-assisted GPS technology, which is a hybrid method that uses a combination of these three methods, is applied. In addition, the positioning technology for determining the location of the terminal infected by the COVID-19 virus is the most common technology of the location-based services, which applies various methods to increase the time and location accuracy that is required for location measurement as a new axis of technology development, and it uses neuron algorithms to enhance the fast and accurate positioning technology.

Artificial intelligence positioning technology (ALDT) is a technology for measuring the location of mobile terminals and has a network-based method for using base station reception signals in telecommunication networks, a handset-based method for using GPS receivers installed in terminals, and a method for proving location by applying neuron algorithms.

The most accurate personal location data value is obtained through the hybrid method. Network-based methods are also very important. This is because location accuracy varies, depending on the size and measurement method of the base station cell in the communication network, and it generally has a measurement error of 500 meters to several kilometers [51].

To overcome these shortcomings, the CNN algorithm and the RNN algorithm in the neuron network are used to increase accuracy. To solve the problem of these two approaches, NA-GPS and ND-GPS technologies are applied, which are a combination of different technologies [52].

Fig. 6 shows Artificial Neural Network Positioning Research Model Design. The positioning technology for the terminal is the most common technology of LBS (Location Based System) and is designed to ensure the accuracy and reliability of these location measurements through various methods in order to increase the time and location accuracy required for location measurement as two pillars of technology development [53-54].

Fig. 6. Artificial Neural Network Positioning Research Model Design

3.3.1. Structural Neural Network Cell ID

The Structural Neural Network CellID technology is the simplest network-based positioning technology that does not require a separate terminal or network change. It has the advantage of identifying the user's location within three seconds, through the service cell ID of the base station to which the user belongs. However, an infrastructure that exhibits large deviations in location information, depending on the size of the cell radius, is designed.

3.3.2. Technical Neural Network Enhanced Cell ID

The Technical Neural Network Enhanced Cell ID method is a technology used mainly in GSM-style mobile phones, which has improved accuracy by adding distance information between base stations and terminals to the Cell ID method. The location of the terminal is located in the cell radius and RTT (3GPP FDD Only) can be used to estimate the radius.

Here, the RTT designs a value that means a limit on response processing time on the device, in terms of the difference between the time the base station requested a

response to the terminal and the time the base station received the response from the terminal.

3.3.3. Artistic Natural Network AOA

The Artistic Neural Network AOA (Angle of Arrival) technology is a technology that provides location information using differences in signal reception angles at three base stations that receive signals from terminals. The most accurate example is the AOA positioning method being applied to VOR systems for aircraft and field military systems. It designs a technology that guarantees an accuracy of 50 to 150 meters (in theory), but actually guarantees accuracy of 150 to 200 meters.

3.3.4. Artistic Natural Network TOA

Time of Arrival (TOA) technology is a technology that obtains location information by utilizing the difference in time of the signal arrival between one service base station and two surrounding base stations that receive signals from the terminal. In other words, each base station has a circle based on the time value of the signal delivery. It is a method that estimates the intersection as the location of the terminal and designs an accuracy of about 125meters.

3.3.5. Technical Neural Network TDOA

The principle of measurement of the Time Differential Network TDOA (LDOA) is used to measure the signal delay of neighboring base stations, based on the signal of the service base station. The measurement of the difference in the signal arrival time between the service base station signal and the adjacent base station signal creates multiple hyperbolic lines, and the principle of estimating the intersection of these hyperbolic lines as the location of the terminal. Generally, it is designed to ensure a position accuracy of 50 to 200 meters.

3.3.6. Structural Neural Network A-GPS

A-GPS (Structural Neural Network A-GPS) is a method of informing base stations of location information sent from satellites by a chip embedded in the device. Even if GPS satellites are used, they are combined with traditional network methods to compensate for these shortcomings, due to the lack of accuracy and usability in urban areas and indoors. In other words, the terminal is designed to measure from satellites and wireless network base stations.

Measurements are collected to measure the location or send the collected information to a PDE, a location measurement system, and the PDE measures and designs the

location of the terminal by mixing the information sent from the terminal and the information generated from the base station.

3.3.7. Digital Neural Network DGPS

The Digital Neural Network DGPS (Differential GPS) method is designed to compensate for errors, according to the position of the satellite obtained by the GPS, to increase accuracy, to install a reference receiver that knows the exact location on the ground, and to compensate for errors in the location signal received from the satellite after receiving a correction signal from the receiver.

3.3.8. Technical Neural Network E-OTD

Advanced Neural Network E-OTD (Electronic Neural Network E-OTD) is a technology that combines network and terminal measuring technologies, and sends radio waves from two or more base stations to the terminal, in order to measure the difference in time when the transmission returns, so the difference in accuracy is not significant. It needs a terminal that supports GPS and provides location accuracy of about 75 to 150 meters and that can also design it.

3.4. Artificial Neural Network Positioning COVID-19 Location Forecast Architecture

To enhance the accuracy of location positioning using artificial neural networks, various algorithms are researched and developed using various optimized T-Tree, B-Tree, and VLC (Visible Light Communication) to communicate with a visible light that flashes at frequencies that are too fast for humans to recognize.

In addition, the artificial intelligence VLC-based positioning method uses these characteristics to assign frequencies that are distinguished by the ID corresponding to each LED and to map the coordinates of each LED. We also use a more accurate cognitive methodology to detect an individual's location information, using Tree information, to detect location information in real time between an individual's location and the location of a person infected by the COVID-19 virus, then reflect the location data of the other person in my location data in real time. One must first compare one party's location information with the other party's location information. **Fig. 7** shows Artificial Neural Network Positioning Research Model Design.

Fig. 7. Artificial Neural Network Positioning Research Model Design

The method of estimating these grids is done by combining them with neuron networks and deriving the coordinates of X, Y, and Z values, and by utilizing rotational values derived from a number of detected positional values to derive the value of Z and device posture values. In the case of N-VLC, the COVID virus line is designed to reduce the margin of error of location values between individuals and to target COVID virus lines, suggesting learning distances for each location through a supportVector Machine (SVM), random forest, K-NNN (K-Nearest Neighborhood), and DT algorithms, which are types of mapping.

3.4.1. COVID-19 Three-Variable Measurement Method

It is equipped with a range-based technology for detection of the COVID-19 virus. In addition, the location of the terminal is found using a three-sided measurement method, based on distance information between an anchor/base station/AP (Access Point), whose location is known, and terminals that have an unknown location. Artificial intelligence neuron algorithms are installed in the existing three-variable measurement method.

Also, the location of the terminal of the COVID-19 Virus, which measures the distance from the terminal to anchor 1, through the artificial intelligence algorithm, and measures the distance to anchor 2, can be found as the intersection of the circle with each distance radiating around each anchor. In addition, in order to find the location of a terminal through artificial intelligence triangulation, it must have at least three pieces of location information in case of a two-dimensional space. In the case of a three-dimensional space, at least four anchors are required. This is because if

the number of circles is less than or equal to the dimensions, one or more points are created.

Therefore, it is most important to accurately measure distance information between terminals and anchors when using distance information-based measurement technology. The distances between terminals and anchors can be calculated by measuring the power of radio signals transmitted from anchors or terminals and the delay time of these radio signals. In addition, the relationship between the strength and distances of the radio signals can generally be defined as a path attenuation model.

Path attenuation models are the strength of the receiving signal at the reference distance between the objects, the path attenuation index, and the distance between the terminal and the anchor. The problem is the indoor positioning system. Compared to outdoor measurement systems, indoor measurement systems have measurement risk factors. In the process of establishing an indoor measurement system, the appropriate coordinates for each anchor are found in advance, and the distance to the anchor can be found by substituting the strength of the signal received from the anchor after finding the terminal. The path attenuation model is measured with artificial intelligence.

However, since the strength of wireless signals in indoor positioning technology is influenced not only by distance, but also by various factors, such as the structure of the indoor space, people, objects, temperature, and humidity, distance measurement using the route attenuation model shows limitations in accuracy.

These limits clearly exist, so they are equipped with neuron algorithms to detect people, things, temperature, humidity, etc.

Currently, artificial intelligence fingerprinting technology is also proposed to find the location of the terminal, considering the characteristics of the wireless signal power according to location, rather than the distance information-based technology, which measures the location after converting the wireless signal power into distance. Thus, fingerprinting, equipped with these algorithms, moves radio signals in the atmosphere at the speed of light (3×10^8 m/s).

Thus, the distance between the terminal and the anchor of the COVID-19 Virus is taken to reach the receiver terminal from the anchor or terminal at the time of transmission, but can be calculated by the time delay of propagation and the multiplication of the speed of light. In general, the measurement of radio delay time between the anchor and the terminal in the interior space is made through

Round-Trip Time (RTT). RTT means the time from when the transmitter transmits the radio signal to the time the receiver receives the signal, then retransmits it and reaches the transmitter.

The time delay between the anchor and the terminal can be calculated in half of the RTT, assuming that the radio signal travels the same path. This is a simple technology that can be applied to a variety of wireless infrastructures, without significant constraints.

However, in Wi-Fi networks, which are currently widely used in indoor spaces, separate servers must be installed in the network for RTT-based technology to be applied, due to problems with the RTT measurement function of the AP (anchor), and for accurate RTT measurement, network latency removal within the measured RTT is essential. For this reason, this thesis proposes an architecture of an artificial.

3.4.2. COVID-19 Virus Low Power Network Based Positioning Architecture

In addition to measuring the distance using the power and propagation time delay of the receiving signal, the distance measurement technology based on the distance information is used to measure the difference in radio time delay and the angle of incidents of the receiving signal from the two anchors in different locations from the terminal, or from the two anchors simultaneously.

The difference in propagation time delay can be converted to the difference in distance between the terminal and the two anchors. Depending on the difference in location and distance between the two anchors, the location of the terminal can be defined as a hyperbolic with a focus on the two anchors.

However, multiple hyperbolic lines are drawn from a variety of different anchor pairs, and the intersection of the hyperbolic lines is determined by this location, called the COVID-19 Virus terminal. The incident angle-based technology defines the position of the terminal as a straight line through the anchor, and it similarly measures the position of the terminal at the intersection of the straight lines drawn, based on several anchors. Fig. 8 shows Artificial Neural Network Positioning Research Model Design.

Fig. 8. Artificial Neural Network Positioning Research Model Design

In addition, many diverse and wireless-based positioning technologies are infrastructures, based on distance information. However, it is difficult to obtain accurate distance information in indoor spaces because the radio signals are scattered and reflected by walls, objects, etc. and they move through multiple pathways. Multi-path signals travel farther than the actual terminal and anchor distance, and have different directions from the original signal. Due to these limitations, the interest in distance information-based indoor measurement technology has now subsided significantly.

Due to the fact that UWB-based positioning technology transmits radio signals to ultra-wide bands of 500 MHz or more, it has strong characteristics in multiple paths and enables ultra-precision positioning in cm units. The Ubisense measurement solution is the most representative UWB-based technology currently in use by many industries and uses radio time delay differences and incident angle information. Although UWB-based positioning technology has the highest accuracy among the wireless-based indoor positioning technologies, it requires expensive equipment (millions of won per sensor, and dozens of sensors are required, depending on the size and complexity of the interior) compared to other technologies, and has the disadvantage of having a complexity high system construction.

ASSIST is a measurement technology based on difference in propagation time delay using acoustic signals. Since sound signals travel at slower speeds than radio signals (approximately 340 m/s at room temperature), distance measurement errors, caused by multiple paths, can be mitigated.

In addition, there is a wave delay-based measurement technology, using a Laser Range Scanner (LRS). This technology measures the position and path of the vehicle by measuring the time the high-precision laser signals that are emitted from the LRS are reflected against the pedestrian or the moving object. Similar to UWB-based technology,

precise measurements in centimeters are possible, but it is difficult to distinguish individual locations in densely populated environments. Using these low-residual network-based positioning systems and designing the architecture, using Newton's algorithm, is essential for combating the COVID-19 virus.

3.4.3. Personal Technology for Location Measurement between COVID-19 Virus Objects

Recent knowledge reasoning techniques use positioning personalization between objects, a technique that infers information that is related to questions or finds answers through a combination of partial information, even if it does not exist directly in the data.

To make a list between a personalized COVID-19 Virus infected person and an uninfected object, location situation information is considered as property for analysis in this paper. Analysis is required to create a list of recommendations among pre-validated objects, and to obtain the data set used in the analysis.

For the convenience of analysis work, all the data investigated was converted to numbers, then stored. The data number is only the order of the data and is not related to the analysis. The age group is divided into 1 for infected people and 2 for non-infectious people, 10 for ages 10 to 20, 30 to 40 for ages 3, 5, 50 to 50 for ages 5, 60 to 60 for ages 6, 60 to 70 and 7 for those in their 70s or older.

Job is expressed as one for students and two for office workers. The three preceding attributes belonging to personal information are objective data, but the three following attributes belonging to contextual information are somewhat subjective, given that they are based on the nature of the information or on the judgment of the individual. Fig. 9 shows Mapping Table for COVID-19.

1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8
2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8
3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8
4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8
5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8
8.1	8.2	8.3	8.4	8.5	8.6	8.7	8.8

Mapping Table

GRID	AP #1	AP #2	AP #3	AP #N
1.3	1.2	3.4	5.7	6.8
2.3	5.2	1.8	7.4	6.2
5.5	3.2	1.5	7.1	2.4
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Fig. 9. Mapping Table for COVID-19

Clearness was expressed as 1 and cloudy as 2. Temperature and feeling were judged by individuals with 9 for the best and 0 for the lowest. Finally, for the method of transportation ($C_i, i=1, \dots, 5$), the value was given by walking, bus, subway, private car, and bicycle. For the analysis of this investigated data, a neuron decision tree was used during the data neuron mining technique.

Due to the fact that the neuron decision tree is already a technique frequently used in the analysis process and is less relevant to the selection of associated rules and pathways between attributes, it was decided that a neuron decision tree was best to be used as a tool for analysis.

First of all, in order to form a neuron decision tree, we need to find the properties that become the top node. The top-level node is selected by the property with the largest information gain value. It is also an algorithm for calculating information gains.

```

-----
#define COVID-19 virus Solve
    CStringattr[Infection] = {"infected person", "noninfectious
    person"};

    void C1_7View::Entropy(double Entro_Age){
    double entropy[] = {0, 0, 0, 0, 0, 0, 0};
    double Job, Age;
    int NUM, valNum;
    for(int j=0; j<TOTALNUM; j++){
    for(int i=0; i< ATTRNUM; i++){
    NUM = Count;
    valNum = AgeCount;
    if(NUM==0||valNum==0) entropy[j] += 0;
    than
    entropy[j] += (double)NUM/COVID-19 TOTALNUM
    *(-(((double)valNum/NUM)*(log10((double)valNum/
    NUM))/(log10(2.)))-(((double)(NUM - valNum)/NUM)
    *(log10((double)(NUM - valNum)/NUM))/(log10(2.))));
    else
    entropy[j] += (double)NUM/COVID-19 TOTALNUM
    *(-(((double)valNum/NUM)*(log10((double)valNum/
    NUM))/(log10(2.)))-(((double)(NUM - valNum)/NUM)
    *(log10((double)(NUM - valNum)/NUM))/(log10(2.))));
    }
    }

    // Information Gain
    eTraffic = Entro_Acc - entropy[0];
    eAge = Entro_Acc - entropy[1];
    ...
    eFeeling = Entro_Acc - entropy[9]; }
-----

```

To calculate the information gain for each attribute, first calculate the expected amount of information required to classify a given sample using (Equation 1). Next, calculate the entropy of each attribute. Let's calculate from the sex of the attributes. The expected amount of information for each distribution is calculated.

For Traffic = 1 : $t_{11} = 56, \dots t_{51} = 32$

$I(t_{11}, t_{51}) = 2.27$

For sex = 1 : $s_{12} = 49, \dots s_{52} = 37$

$(s_{12}, s_{52}) = 2.25$

If the samples are divided according to gender (sex), using the expected amount of information required to classify a given sample is necessary. Therefore, the information gains from the segmentation are also found.

In the same way, the information gains from the remaining attributes are calculated and the properties with the highest information gains are selected as the test properties. In this paper, the infected person was chosen as the first test property.

A new node is created, the move method is labeled, and the branches are generated for each value of the attribute. Then, the samples are divided as they appear. This creation of a decision tree allows a personalized list of recommendations for a user's request. For example, suppose you recommend a restaurant to a user with the same personal and contextual information. To create a COVID-19 infection list from the user's data, go down the tree. In the first node, attributes for infection, age, movement path, and sensitivity are determined for the user.

In the second node, the attributes for the job considered will go down to the left because the user is a student. In this way, when you reach the last node of the tree (the 20th node at the last level) you will generate a list of recommendations based on the rate of pathways for the infected individuals. Recognizing the difference between the object and the object in the highest proportion of the movement path, the error between the objects is generated according to the list of targets of the infection, and each weight is assigned for use in the weight application stage. The analysis result, recommendation list, and application of infection weight were shown.

3.4.4. Personal Technology for Location Measurement between COVID-19 Virus Objects

This is a step in which personalized recommendation lists and location-based recommendation lists are aggregated by applying weight values to each point in the list of objects. At this stage, the weighting was given a value of 0.8 and 0.3 to the personalization recommendation list and the location-based recommendation list. To find the optimal weighting value, experiment in 0.11 units until a value of 0.8 and 0.3 is given to each. The most appropriate value of weight is when the accuracy of the recommendation is assessed to indicate the highest accuracy. The calculation that points to the restaurant by applying the weight is as shown in the following expression.

$$N1 = a_i * I_p + e_i * h_i$$

"Ni" is the score for the weight of the "i" first route, "ai" is the point from the list of individual ages, and "Ip" is the weight value to be applied to the list of individual occupations. In addition, "ei" is the value for the weights obtained from the location-based recommendation list and "hi" is the approximation of the weights to be applied to the location-based recommendation list. When the value of the weight applied is 0.4 and 0.9 respectively, the following calculation is made:

$$N1 = 10 * 0.8 + 20 * 0.3 = 32$$

Get the approximation, 20, from the personalization recommendation list and the point, 30, from location-based recommendation list. The multiplication of the weight gives the final point, 36, and other restaurants calculate the final point in the same way. Below, the final points were calculated by reducing the weights by 0.1 for the personalization recommendation list, and increasing them by 0.1 for the location-based recommendation list in order to set the optimal weight value.

When the final point is calculated by applying the weight, it is recommended to track and manage that the point is not a COVID-19 virus in the order in which the points are high. It also makes a difference in the list of recommendations based on weight changes. This paper got the best evaluation when the resulting value applied 0.3 weight to the personalization recommendation list and 0.9 weight to the location-based recommendation list. In other words, the user will be given the second of the final recommendation lists.

3.5. COVID-19 Positioning Diagram (Class Diagram)

CodCOVID-19 Inherit for the work of CString, Double and Double(job) of Virus. And TypeCheckVistor gets the value of SetState, GetState among objectState. Also, the value of Double (Virus) and Log (Virus) of the valNum and the valEntropy is received Fig. 10.

Fig. 10. UML Diagram for COVID-19 Virus Location

4. EXPERIMENTS AND RESULTS

4.1. Experiment Environment and Data Set

The experiment in this paper was conducted using the Python program and Microsoft Windows 10 pro, and the experimental environment was a system of Pantium i7 3.2 GHz, 1024 MB RAM. Data used in a number of tests were collected through investigation. The survey was verified using the location data of public data with multiple pieces of location information. It also includes location information and demonstrates the efficiency of the system between objects for infections of COVID-19. In addition, the recommended system interfaces used in the experiment are shown below, representing data not considered for location of mobility and data considered.

4.2. Test Evaluation Method

To prove the accuracy of the recommendation system, considering the personalization and location information at the same time, the data sets collected using the K-fold cross-validation method are classified and tested as learning data and test data. In the K-overlapping method, the initial data is randomly divided into a subset of “n1” and “k” of roughly the same size. Learning and testing are repeated “k” times. In the “i-th” iteration, the subset “ni” is used as a test set and the rest as learning data. Accuracy estimates are the total number classified correctly from “k” iterations, divided by

the number of samples in the initial data (re-realization rate, Recall).

R = the overall number of correct recommendation total number of samples

Performance is also evaluated by measuring the mean absolute error rate in “k” tests. The mean absolute error rate can be said to be more accurate only when the predicted evaluation value is minimized. If the actual point value of the target set is $\{r1, \dots, rn\}$, then the predicted point value is expressed as $\{p1, \dots, pn\}$, and if the error $E = \{e1, \dots, en\} = \{p1 - r1, \dots, pn - rn\}$, then the mean absolute error rate is obtained.

To prove the accuracy of the recommendation system considering personalization and location information at the same time, the data sets collected using the K-fold cross-validation method are classified and tested as learning data and test data. In the K-overlapping method, the initial data are randomly divided into a subset of “n1”, ... and “k” of roughly the same size. Learning and testing are repeated “k” times. In the “i-th” iteration, the subset “ni” is used as a test set and the rest as learning data. Accuracy estimates are the total number classified correctly from “k” iterations, divided by the number of samples in the initial data (re-realization rate, Recall).

The experiment first made a performance comparison between the COVID-19 recommendation system between objects, taking into account only existing personal information and situation information, and the location-based personalized recommendation system proposed in this paper.

In addition, experiments were conducted to obtain optimal weights for comparing accuracy with the COVID-19 virus infection recommendation system and simple recommendation system, considering weight. Finally, by comparing the performance of the existing recommendation system with the proposed recommendation system and the weighted recommendation system, the excellence of the system proposed in this paper is proven.

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19 virus infection recommendation system and the simple recommendation system considering weight. Finally, by comparing the performance of the existing recommendation system with the proposed recommendation system and the weighted recommendation system, the excellence of the system proposed in this paper is proven.

4.3. Performance Comparison

Through the above two experiments, the excellence of the error verification system, which was personalized in case of the COVID-19 infection of the neuron engine-based positioning service, and location information, rather than personal information or situation information, were measured to prove real-time reliability. Monitoring Query Management (MQM) is a moving query management function, Partitioning Query Index (PQI) is a small split operation, and BQR-tree method (denoted by BQRT) refers to a tree structure algorithm.

As shown in Fig. 11, the CPU Time (ms) shows a value of 10 when the number of moving object is simulated 10 times. There is also a value of 130 when the CPU time is 35 days. Space Partitioning Query Index (SPQI) is the CPU Time (ms) and when it is 35, it comes out to be about 10 or 130 or so. Also, the value can be seen at 20 for the CPU Time (ms) 5 and 130 for the CPU Time (ms).

Fig. 11. Number of Moving Object (x 10)

Also, as shown in Fig. 12, the CPU Time(ms) shows a value of 10 when the number of moving objects is simulated 1,000 times. When the CPU time is 90, there is a value of

130. So the performance of the CPU has improved even more. SPQI is the CPU Time (ms) and when it is 25, it comes out to be about 130cm. Also, the value can be seen at 30 for the CPU Time (ms) 5 and 130 for the CPU Time (ms). So, we can see the difference between 10 simulations and 1,000 simulations.

Fig. 12. Number of Moving Object (x 1,000)

5. CONCLUSION AND FUTURE WORK

The purpose of this paper is to reduce the error rate by dividing the infected and non-infected persons within the error range between objects, based on their location, considering the mobility of users, due to the emergence of the COVID-19 virus. In addition, performance was evaluated through necessary experiments.

With the recent development of internet and mobile, it was applied by using portable devices and wireless computing technology with excellent GPS and wireless data transmission capabilities. So, it tracks the location based on the GPS, Wi-Fi, and 5G data of the smartphone among the personal denture information to verify the infection route of city-based COVID-19 to the smart city. In the analysis process, the decision tree technique, which is one of the data mining techniques, was used among techniques known to be null. In addition, a weight is introduced into each recommendation list in order to provide the combined optimal recommendation service through personalized location-based tracking. Recently, many disasters have occurred. In particular, COVID-19 is the strongest of many

disasters in recent years. However, the world is also overcoming COVID-19, in accordance with the era of the 4th Industrial Revolution. In preparation for the COVID-19 outbreak, this paper uses a moving query object and a virus tracking system to move objects, based on smartphones that are spread worldwide using LBS systems, such as Wi-Fi, 5G, and GPS.

We are tracking and trying to increase CPU performance for these tracking systems. So, we made a COVID-19 Location-Based Research Model, based on artificial intelligence and present Artificial Neural Network Positioning Research Model Design. Also, based on the presented model, Artificial Neural Network Positioning COVID-19 Location Forecast Architecture was designed.

The CPU Time (ms) is higher when the number of moving objects is simulated 1,000 times, and when the MQM CPU time is 5, it shows a value of 10. When the CPU time is 90, there is a value of 130. So, the performance of the CPU was improved further. SPQI is the CPU Time (ms), and when it is 25, a value of about 130 is displayed. In addition, in the case of BQRT, you can see a value of about 30 for the CPU Time (ms) 5 and 130 for the CPU Time (ms). So, you can see the difference between 10 and 1,000 simulations.

Finally, a simulation was applied to this tracking, and 10 and 1,000 experiments were conducted for comparative analysis. Therefore, we study to increase active tracking and performance when the COVID-19 virus and other disasters in the future occur in smart cities.

Declarations

Conflict of interest: Authors don't have any financial relationship with an organization that sponsored the research and didn't receive any compensation or consultancy work. There aren't any potential conflicts of interests that are directly or indirectly related to the research.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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