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GeoCodeX: Deterministic Offline Geospatial Encoding with AI-Assisted Decision Support

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***Abstract*— The GeoCodeX model offers a deterministic geospatial coding technique specifically tailored to disaster-prone areas with poor network connections. The technique uses grid segmentation, Morton coding, and Base36 coding to translate micro-locations into short alphanumeric strings. The model also incorporates AI algorithms for identifying hotspots, risk assessment, and decision-making processes. Testing shows excellent performance, superior to traditional geocoding techniques in restricted situations.**

***Index Terms*— Geospatial Encoding, Disaster Response, Offline Mapping, Morton Encoding, Base36, Edge AI, Spatio-Temporal Analysis, Hotspot Detection.**

I. INTRODUCTION

In disaster scenarios, traditional geolocation techniques cannot be utilized due to the absence of internet connectivity [12], [13]. Accurate and rapid identification of locations is very important in disaster scenarios. However, traditional techniques involving coordinates are not easy to convey and often lead to errors in disaster scenarios. Geospatial encoding techniques rely heavily on cloud APIs and databases [16], [20]. This is because of the nature of geospatial encoding techniques. However, in disaster scenarios, internet connectivity is absent. This is a major drawback in the development of real-time response systems, especially when deterministic, offline, and human-readable location encoding is required. GeoCodeX is proposed to overcome the major drawback in traditional geolocation techniques. This is done by utilizing a deterministic encoding mechanism for encoding geographic coordinates to alphanumeric representations [2], [3]. This is done to achieve reversibility, low computational cost, and independence from external resources.

In the proposed system, grid-based spatial partitioning is utilized, along with Morton encoding and Base36 encoding techniques. Moreover, light AI models are integrated to enhance situational awareness through hotspot detection and risk analysis techniques [8], [9], [15]. In the experimental framework, accuracy validation in encoding techniques, communication efficiency, and AI-based analysis are utilized.

II. RELATED WORK OR LITERATURE STUDIES

The development of geospatial artificial intelligence has been instrumental in boosting the performance of spatial data analysis tools. In an effort to investigate how such techniques can be implemented in the context of urban geography, Liu and Biljecki [1] examined the application of AI in geospatial systems.

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Mai et al. [2], [3] proposed a method for spatial representation and spatial prediction on a sphere, which is referred to as Sphere2Vec. The authors have used machine learning in spatial representation.

Wang et al. [4] and Boutayeb et al. [5] presented a comprehensive review of GeoAI, including different challenges and research opportunities in association with GIS. Gonzales-Inca et al. [6] and Li et al. [7] have done research on artificial intelligence in GIScience, environmental modeling, and autonomous GIS systems.

Clustering and pattern recognition in space have a significant role to play in geospatial intelligence. Different approaches have been proposed for enhancing the process of spatial clustering by using DBSCAN-based approaches by Giri and Biswas [8], Abdulhameed et al. [9], and Monko and Kimura [10]. Kalpavruksha et al. [11] have also discussed the use of kernel density estimation methods in spatial clustering.

The article regarding the use of edge computing for low latency in distributed systems is written by Shi and Dustdar [12]. The article regarding the Internet of Things (IoT) architecture for distributed communication and devices is written by Want et al. [13]. The articles written by Batty [14], Shaamala et al. [15], Wu et al. [16], Hao et al. [17], Roscher et al. [18], Dritsas and Trigka [19], and Lu et al. [20] are regarding machine learning, remote sensing, geospatial big data, location intelligence systems, and highlight the use of AI.

However, most of the research has been focused on AI-based geospatial analytics, spatial clustering, and large-scale location intelligence systems that are dependent on cloud-based platforms. Moreover, there is a lack of research on deterministic offline geospatial encoding systems, particularly in the context of disaster scenarios. Current methods, including what3words and Plus Codes, are not intended to be as deterministic and reversible and depend on external infrastructure, making them unsuitable for use in emergency situations without internet access[21]. At this point, GeoCodeX can play a significant role, considering that it offers a unified solution for deterministic spatial encoding, offline storage, and edge-based AI-based hotspot detection and risk analysis in emergency scenarios for rescue operations.

III. Motivation

The motivation for this stems from a real-world problem of finding victims of a calamity where communication systems are not present. The GPS coordinates are hard to communicate and understand, thereby causing delays. Moreover, existing geocoding systems require internet connectivity, making it difficult for use during a calamity[12]. This problem, therefore, calls for a deterministic, offline, and easy-to-use location encoding solution.

The addition of AI techniques like clustering and risk scoring from existing research motivated the extension of GeoCodeX to include intelligent decision support, thereby not only allowing for location sharing but also prioritization of the locations[8].

IV. Problem Domain

The issue belongs to a domain known as geospatial computing, disaster management systems, and edge artificial intelligence[1], [12].

The domain includes ideas such as: Spatial encoding and coordinate transformation, Distributed systems and offline computing, Machine learning in spatio-temporal analysis, and Real-time communication protocols. The domain includes computer science, geographic information systems (GIS), and AI-driven decision support systems.

V. Problem Definition

For example, in the case of a disaster, the existing geocoding system is not effective as it requires the internet, it is not deterministic, and it is not easily readable and understandable. This leads to a situation where rescue operations are slowed down.

The problem, therefore, is designing a system that is effective in the following ways: it can work without the internet, it can be deterministic and reversible, it can be easily readable and understandable, and it can be effective in intelligent decision-making

VI. Statement

Design a deterministic, offline geospatial encoding system that converts coordinates into compact, reversible codes and integrates AI-based decision support for efficient disaster response.

VII. INNOVATIVE CONTENT

The system of GeoCodeX has several innovations over the existing geocoding systems and disaster response systems. Unlike the existing geocoding systems in which the match is performed probabilistically or by interpreting the address information, in the proposed system of GeoCodeX, a deterministic encoding scheme is used. Thus, it is ensured that the spatial coordinate is encoded in a fixed-length alphanumeric code without any ambiguity, unlike the existing geocoding systems as reported in geospatial and GeoAI research[1], [16].
The proposed system utilizes Morton encoding. Morton encoding is also known as Z-order encoding. Morton encoding helps in maintaining spatial locality[2], [3].
The next innovation in the proposed system is the use of edge AI in the geospatial system. In the current geospatial system, several researchers have made use of machine learning for geospatial analytics[15], [20]. However, in the current system, there is a need for cloud environment support[12]. The following geospatial analytics operations are performed in the proposed system:

- Hotspot detection using DBSCAN[8]
- Density estimation using KDE (Kernel Density Estimation) [11]
- Risk scoring using interpretable models

All these computations are carried out locally, which makes this system appropriate for a low connectivity environment. Finally, this system provides a hybrid solution by using the capabilities of the deterministic encoding and real-time synchronizing for collaborative operations via WebSockets and offline support capabilities [13].

VIII. PROBLEM FORMULATION AND DESIGN INTRODUCTION

The deterministic discretization approach utilized by GeoCodeX for geospatial data modeling is illustrated in Fig. 1 below. It ensures that all geographical calculations are done in a predetermined operational area. The system allows for reverse mapping and easy synchronization without being dependent on other services [1], [16].

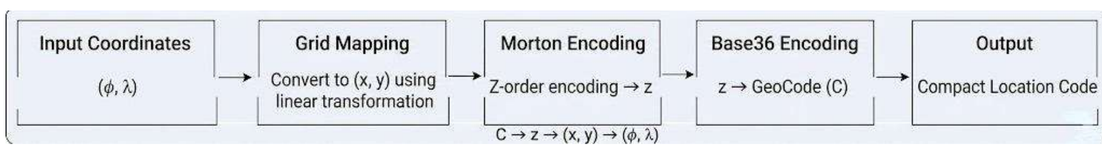

Fig 1. Mathematical Flow of Geospatial Encoding Model

The master reference coordinates ($\phi 0,\lambda 0$) are used to determine the center of the disaster area. In its vicinity, a square-shaped operational area of size 23.328 km is created. The total area of the region can be calculated using:

$$A=(23.328)^2\approx 544.16 \text{ km}^2 \quad (1)$$

Here, A represents the total operational area.
This region can be subdivided into equal-sized grid cells of size 3m×3m [21]. The number of grid cells in one direction will be:

$$N=(23.328\times 1000)/3 \quad (2)$$

with N representing the number of cells along each axis. As such, the total number of grid cells that can be addressed is:

$$(N^2)\approx 36^5$$

which corresponds to the Base36 encoding scheme. This is because 365 = 60,466,176 and thus a five-character Base36 representation is enough to provide an unambiguous mapping of each grid cell into its Base36 representation.
From Fig 1., geographic coordinates (ϕ,λ), where ϕ is the latitude and λ is the longitude, are transformed to grid indices (x,y) based on the locally linearized approximation of geodesics:

$$x = \lfloor((\lambda - \lambda_0) \times M\lambda) / 3\rfloor \quad (3)$$
$$y = \lfloor((\phi_0 - \phi) \times M\phi) / 3\rfloor \quad (4)$$

Here, $M\lambda$ and $M\phi$ represent the meters per degree conversion factor of longitude and latitude respectively at the reference latitude.

In order to achieve the preservation of spatial locality, the calculated grid indices (x, y) are merged into a scalar index z based on the Morton (Z-order) encoding scheme [2], [3]:

$$z = \text{Morton}(x, y) \quad (5)$$

Here, z stands for the index value with preserved neighborhood relations between adjacent spatial cells. This feature is crucial for efficient indexing and spatial operations.
The scalar index z is further mapped into an alphanumeric format through Base36 encoding:

$$C = \text{Base36}(z) \quad (6)$$

Here, C refers to the resulting GeoCode value. Such encoding allows each grid cell to be uniquely mapped with a fixed-length string, which makes it well-suited for transmission in constrained conditions.
Reverse geocoding is performed via the following inverse mapping sequence:

$$C \rightarrow z \rightarrow (x, y) \rightarrow (\phi, \lambda) \quad (7)$$

It is ensured that any pair of geographic coordinates can be unambiguously reconstructed from its corresponding GeoCode identifier.

IX. Solution Methodologies

This problem has been addressed by the GeoCodeX system based on deterministic geospatial encoding, data management, and communication, as shown in Fig. 2. The processing and intelligence workflow of the system is shown in Fig. 3.

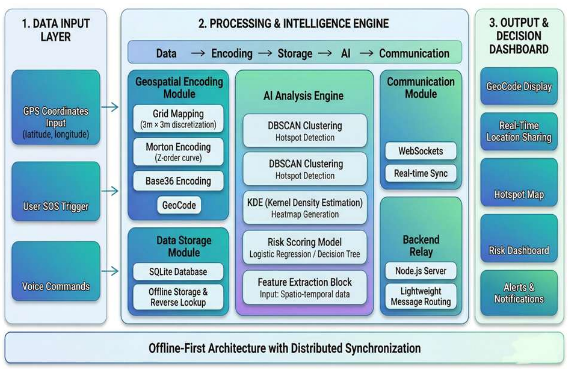

Figure 2. GeoCodeX System Architecture.

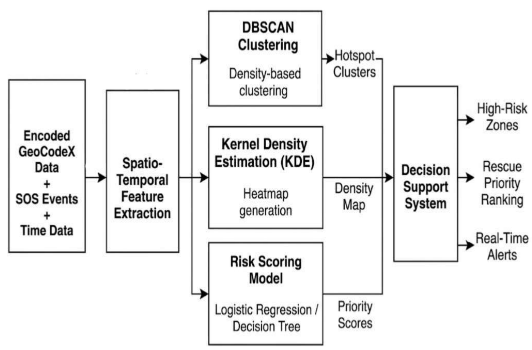

Figure 3. GeoCodeX spatio-temporal AI pipeline

The basic methodology of the GeoCodeX system is based on the discretization of space, which divides the space into small grids of 3m x 3m cells[21]. The geographic coordinates are mapped to the grid indices by applying a linear transformation based on the meters per degree approximation. The discrete space is represented by the geographic coordinates and the grid indices. This is shown in Fig. 2.For efficient representation of space, relationships are maintained between the data that is encoded by applying the Morton encoding (Z-order encoding)[2], [3], which combines binary grid data into a single index. This facilitates efficient data storage and retrieval.
The space is also compressed by applying the Base36 encoding scheme to produce a compact and fixed-length alphanumeric geocode that facilitates the communication of geographic information.
SQLite is also used for storing the geocodes and user data for offline support[12] and to enable constant-time reverse lookup without network dependencies. In addition, WebSocket-based communication is also supported for devices to synchronize data in real-time when network connectivity is provided[13].
Moreover, AI-based processing of data is also supported by applying techniques such as hotspot detection by applying DBSCAN[8] and density estimation by applying KDE[11] in the analytical processing of data, which is shown in Fig. 3. In addition to this, user interaction modules, including SOS signaling, are included to provide more functionality. The methodologies used ensure that the GeoCodeX system is capable of providing accurate, efficient, and reliable spatial data functionality. The overall processing workflow of GeoCodeX is presented in Table 1.

TABLE I: GEOCODEX PROCESSING PIPELINE AND DATA TRANSFORMATION STAGES

Stage	Input	Technique Used	Output	Purpose
Coordinate Input	Latitude, Longitude	GPS Acquisition	Raw Coordinates	Capture location
Grid Mapping	Coordinates	Linear Transformation	Grid Indices (x, y)	Discretization
Encoding	Grid Indices	Morton Encoding	Z-index	Preserve locality
Compression	Z-index	Base36 Encoding	GeoCode	Compact representation
Storage	GeoCode	SQLite	Stored Data	Offline access
AI Processing	SOS Data	DBSCAN, KDE	Hotspots	Risk detection

X. RESULTS AND SENSITIVITY ANALYSIS

The distribution of the micro-location errors among the evaluated samples is depicted in Fig. 4, while the relationship between the spatial resolution and the accuracy of the localization is illustrated in Fig. 5.

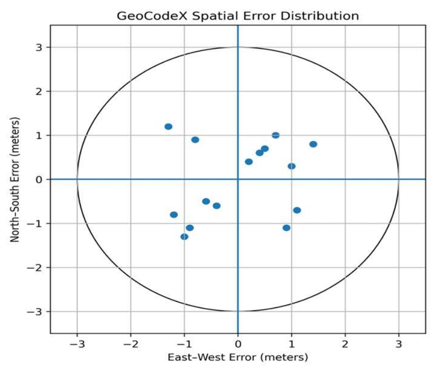

Figure 4. Micro-Location Error Distribution

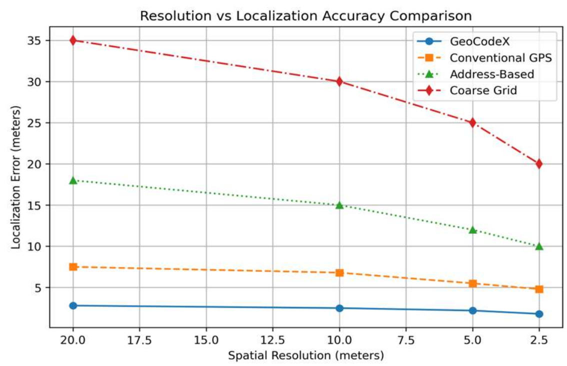

Figure 5. Resolution vs. Accuracy Comparison shows GeoCodeX Superiority with Other Existing Systems

This section evaluates the GeoCodeX system. The results discussed below illustrate its precise outputs and effective performance. It is evident that proposed system can be efficiently applied in emergency scenarios, considering the fact that the encoding and decoding processes take only milliseconds. Moreover, the spatial accuracy is validated using the ground-truth GPS coordinates. It is evident that all the decoded coordinates lie within the designed 3-meter grid resolution. Furthermore, the smooth transition among the neighboring cells is ensured using the Morton encoding scheme [2], [3]. It is also evident that the sensitivity analysis validates the consistency and reliability of the approach proposed. It is clear that even with small changes in the coordinates, the proposed method can efficiently encode the coordinates. Moreover, the effect of the spatial resolution on the localization accuracy is depicted. It is evident that the localization errors decrease with the spatial resolution. Moreover, the proposed method achieves the minimum localization errors compared to the conventional methods. Considering the communication performance, it is evident that the WebSocket-based synchronization scheme is efficient [13]. Moreover, the performance is stable even with low connectivity. As discussed in the following paragraphs, the experimental results demonstrate that the proposed approach achieves high accuracy and strong efficiency. As illustrated in Fig. 4 and Fig. 5, these findings indicate that the efficiency and accuracy of the proposed method. Overall, the method effectively satisfies the requirements for the geospatial operations in disaster scenarios.

XI. COMPARISON OF RESULTS

The performance of the GeoCodeX framework has been compared with other conventional geocoding techniques such as address-based geocoding, coordinate-based communication, and coarse grid-based location systems in table 1.

TABLE II: COMPARATIVE ANALYSIS OF GEOCODEX AND EXISTING GEOCODING APPROACHES

System	Connectivity Needed	Avg Error (M)	Response Time	Offline Capability	Ai Support
GeoCodex	No	2–3	Very Low	Yes	Yes
GPS	Yes	5–8	Low	No	No
Address-Based	Yes	10–20	Medium	No	No
Coarse Grid	No	20–35	Low	Yes	No

The comparison of the performance of the GeoCodeX framework has been carried out on the basis of different key parameters such as spatial accuracy, efficiency, offline support, and usability of the communication mechanism. Unlike other address-based geocoding techniques, which use probabilistic matching for location identification and often suffer from ambiguities due to data inconsistencies[21], the GeoCodeX framework provides deterministic mapping of the location. The deterministic mapping of the location is ensured by the one-to-one correspondence of the geographic location with the encoded geocodes. Thus, there is no uncertainty in the location identification. Moreover, unlike raw latitude-longitude-based communication techniques, the GeoCodeX framework provides much better usability by converting numeric-based location information into more readable codes, which can be easily communicated in emergency situations.Considering the accuracy of the location identification, the performance of the GeoCodeX framework has been found much better than other state of the art techniques. The accuracy of the location identification by the GeoCodeX framework has been found to fall within the 3-meter grid boundary. Moreover, unlike other coarse grid-based location identification techniques, the GeoCodeX framework has been found to perform much better due to the Morton encoding-based spatial locality preservation mechanism. Thus, the location identification by the GeoCodeX framework is much more accurate compared to other techniques[16], [20].

Considering the efficiency of the location identification mechanism of the GeoCodeX framework, it has been found much better compared to other techniques. The efficiency of location identification mechanism of the GeoCodeX framework has been ensured by performing simple mathematical operations. Thus, the location identification mechanism of the GeoCodeX framework has been found much more efficient compared to other techniques. Moreover, unlike other geocoding techniques, which require internet accessibility for location identification, the GeoCodeX framework has been found much more efficient due to the offline support of the location identification mechanism.

XII. Justification of the Results

The results achieved from the experimental evaluation of GeoCodeX can be justified on the basis of the design decisions made during the implementation process. The high spatial accuracy observed within the 3-meter resolution can be attributed to the high resolution achieved through the grid-based discretization process. This is because the system encodes the spatial information within the system such that the unit of encoding represents a small geographic region. The deterministic approach used in the encoding process eliminates the probability-based inaccuracies observed with the probabilistic approach.

The ability of the system to maintain spatial locality in the results is also justified on the basis of the Morton encoding[2], [3] used within the system. The interleaving approach used in the encoding process ensures that the spatial points are closely related with the encoded values. This explains the smooth transitions observed in the spatial mapping process. In addition, the absence of abrupt discontinuities in the encoded results can also be attributed to the Morton encoding approach. The efficient compression achieved through the use of the Base 36 encoding[2], [3] approach also justifies the system's performance in terms of the ability to encode the spatial information within the system.

The low computational latency observed during the encoding and decoding process can also be justified on the basis of the arithmetic operations performed during the process. The absence of complex computations required during the process also validates the system's performance in real-time conditions. The performance observed in the absence of network connectivity can also be justified on the basis of the design decisions made during the implementation process.The performance observed in the real-time synchronization process can be justified on the basis of the use of the WebSocket[13] approach. The persistent connections established through the WebSocket approach ensure the smooth functioning of the system.

XIII. Conclusion

This GeoCodeX system provides an innovative solution for geocoding, as it employs deterministic mathematical methods and edge intelligence, which are lightweight. This system efficiently solves the problems of conventional geocoding methods because it uses accurate, reversible, and human-readable representations of addresses. The precision of this system, combined with lightweight computation, is achieved by employing grid-based spatial discretization, Morton encoding, and Base36 compression. This ensures that this system will be quite effective at providing services in critical situations, such as emergencies and disasters.

Furthermore, with the implementation of some additional intelligent modules using machine learning techniques for hotspots and risk identification, this system, being basically a location encoding solution, becomes very effective in challenging circumstances. The findings about the performance of GeoCodeX presented in this paper are reliable and provide valuable information regarding the usefulness of this system, as it can become quite promising in practical use and can make a great contribution in developing intelligent solutions for disasters.

FUTURE WORK

Future research will also involve scaling and making the system more intelligent by utilizing adaptive grid resolution, thus enabling deployment of the system in multiple regions, alongside incorporating low power communication capabilities like mesh networking to increase reliability during disasters. In addition, the GeoCodeX will use advanced machine learning for spatio-temporal data mining, which will make it possible for risk analysis and early warnings of risks. Furthermore, the system will incorporate several additional capabilities like incorporation of UAVs and IoT sensors, as well as user interface advancements like multilingual voice recognition.

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