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CSINR: Interconnected nodes reading for accurate GPS precision and mapping to achieve geographic centric self-learning nodes

[1]N. Swaroop Kumar, [2]K.S. Ramesh , [3]A.Maheswary, [4]R.Revathi

[1]Research scholar, Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, A.P, India, swaroopa7@gmail.com

[2]Professor, Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, A.P, India-522502. dr.ramesh@kluniversity.in

[3]Associate Professor, Department of ECE, Sri Venkateswara College of Engineering & Technology, Chittoor-517127. maheswaryswaroop@gmail.com

[4]Associate Professor, Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, A.P, India. rrevathi@kluniversity.in

Abstract – Global Positioning System (GPS) provides a reliable solution for accurate mapping and geographical labeling. The coordination of nodes in communication are wider and has a centralized monitoring cum reporting ecosystem. These nodes fail to label the inter-connected object spaces between reporting agents and nodes using integer ambiguity based satellite to node coordination. The time delay of Total Electron Content (TEC) is computational higher. In this article, a dedicated GPS clock prediction based precision and mapping is conducted for an interconnected nodes. The technique uses a novel technique of Centric Self-Learning Interconnected Nodes Reading (CSINR) for validating the GPS accuracy and precision. The interconnected nodes are dependent on the information shared via network managers and hence, CSINR technique extracts the nodal relationship of interconnected nodes to build a pseudo connected network based on temporal factors and clock offset. The technique is further supported with a self-learning nodes approach, with each node extracts the principle value of supporting neighboring nodes to maintain reliable source accuracy information. The proposed technique has achieved an evaluation ratio of 97.32% in precision and 92.78% in sensitivity of node occurrence. The overall technique has proposed 97.43% accuracy over the cluster of 32 nodes and 97.12% in cluster of 64 nodes respectively.

Keywords – GPS mapping, GPS Precision, geographic centric self-learning, GPS accuracy

I. Introduction

The communication of a peer to peer is bound to frame a static connection for stable networking using multi-dimensional attributes and functions. Typically, the current ecosystem, of networks is based on the fundamental connections and parametric infrastructural setup, the role of Global Positioning System (GPS) is vital in making the overall networking stable and trackable. Based on the GPS coordinates, multiple applications, services and techniques are developed to provide a reliable environment. The GPS terminology was to provide a paper-less transportation logs and record under a dynamic updating ecosystem [1], the approach is to assure the overall node movement is tracked and monitored for a given route or path. With time, the GPS parameters has improved under various multi-disciplinary data extraction. Today, the role of GPS has extended to track a data movement, provide recommendations of services and information of a particular event or a place. In general, these services are developed with time and has enhanced the approach of GPS utilization.

The major challenge in current times is to provide a reliable accuracy in GPS coordinates in-order to justify the recommendation services. [2] a detailed comparison and survey is reported on various computation and precision accuracy of GPS. The process has improved with smart-phone tracking based evaluation [3]. The smart-phone based GPS coordinates correction and tracking has a challenging task, as each coordinates associated with the smart-phones are dynamic and has a rational change of information prediction. This makes the GPS to be vulnerable under certain extreme cases and scenarios such as crowd node polling, GPS conjunction controlling and management. The process has to assure the overall GPS coordinates are reliable and mapped to a particular antenna for services. In current high-fast communication era, the GPS accuracy and prediction of precision is a challenging approach. In this research article, a systematic study is proposed and evaluated to provide a reliable solution and framework for GPS accuracy prediction. The research article discuses a brief survey on existing systems and techniques in section II, followed by a proposed methodology design and a proof of concept using a mathematical approach in Section III and IV respectively. The results and discussion are summarized with the findings and observations made under the experimental setup in Section V followed by conclusion and future scope remarks.

II. Literature Survey

The Global Positioning System (GPS) is a reliable source for tracking and monitoring the nodes movement and location based on geometric coordinates. Typically, various techniques and approaches are designed and developed for a reliable and secure mode of GPS tracking. With advancement of technology, the vulnerabilities in GPS has increased under multiple cyber-physical attacks such as black-hole monitoring, spoofing and unauthorized coordinates tracking. This has proposed a series of tracking and monitoring units of GPS as discussed in [4], the passive GPS coordinates are the residual coordinates generated from the log-records of multiple nodes and devices. The authors have developed a reliable framework to handle multiple instrumental nodes for correction under long-term travel behavior approach. This provides the GPS system a reliable support for assuring the data is trackable and has an authentic permission for accessing the coordinates. The process of generated a large volume of data via these processes. [5] has discussed a big-data management approach for optimizing the data collection and GPS coordinated accuracy mapping.

Further a detailed processing and analysis of information mapping and reliability understanding is processed and evaluated to generate a secure GPS location accessing. In [6] the Standard Positioning System (SPS) is proposed and discussed. The SPS provides a generalized representation of overall coordinates associated for communication and hence a centralized monitoring is unassessed, to overcome the challenge a dedicated monitoring and positioning system is required for evaluation [7]. A customization and processing approach for improved behavioral mapping in GPS based outset is evaluated. These customizations are predominant and has influence of coordinate recommendations for modern technological assistance. The agenda of information breeching through multi-agent information sharing systems has to be optimized and generate a system interlocked approach for data transfer as in TelMED [8] for secure and reliable data communication using inter-domain information systems.

The geometric parameters of information collection via GPS coordinates are evaluated under a timely manner based paradigms [9] to assure the dependency of time and coordinates under the operations. The fundamental concept behind this approach is to secure the data dependency under open channel communication line. Hence with the overall analysis a report of GPS growth and dependency is drafted in [10] to project the need and challenges for GPS processing and development in near future. The Further, the low cost GPS tracking [11] is proposed and developed to make the system more reliable and agile in customizing the incoming request and location accessing permissions. The agenda of current GPS coordination mapping and polling is to secure a reliable permission and dependency for mapping an accurate GPS location based on a self-learning recommendation system. The recommendation systems of ICT and [12] its role for customizing the networking system is a major challenge for improvising the communication ecosystem. The current research statement is to provide a systematic evaluation scheme for improving the conditions on GPS coordinate recommendations and mapping.

III. Proposed Methodology

The terminology of proposed system is to improve the specification and approach of inter-node reliability for an accurate mapping of GPS coordinates. Technically, the process of defining and acquiring the GPS coordinates is bound with respect to the Node Attribute Extraction (NAE). The NAE fetches the initial parameters of an active node via a shared antenna under the communication standards and operational principles. Technically, the location of users (U_n) is inter-connected into a stream of nearest location binding.

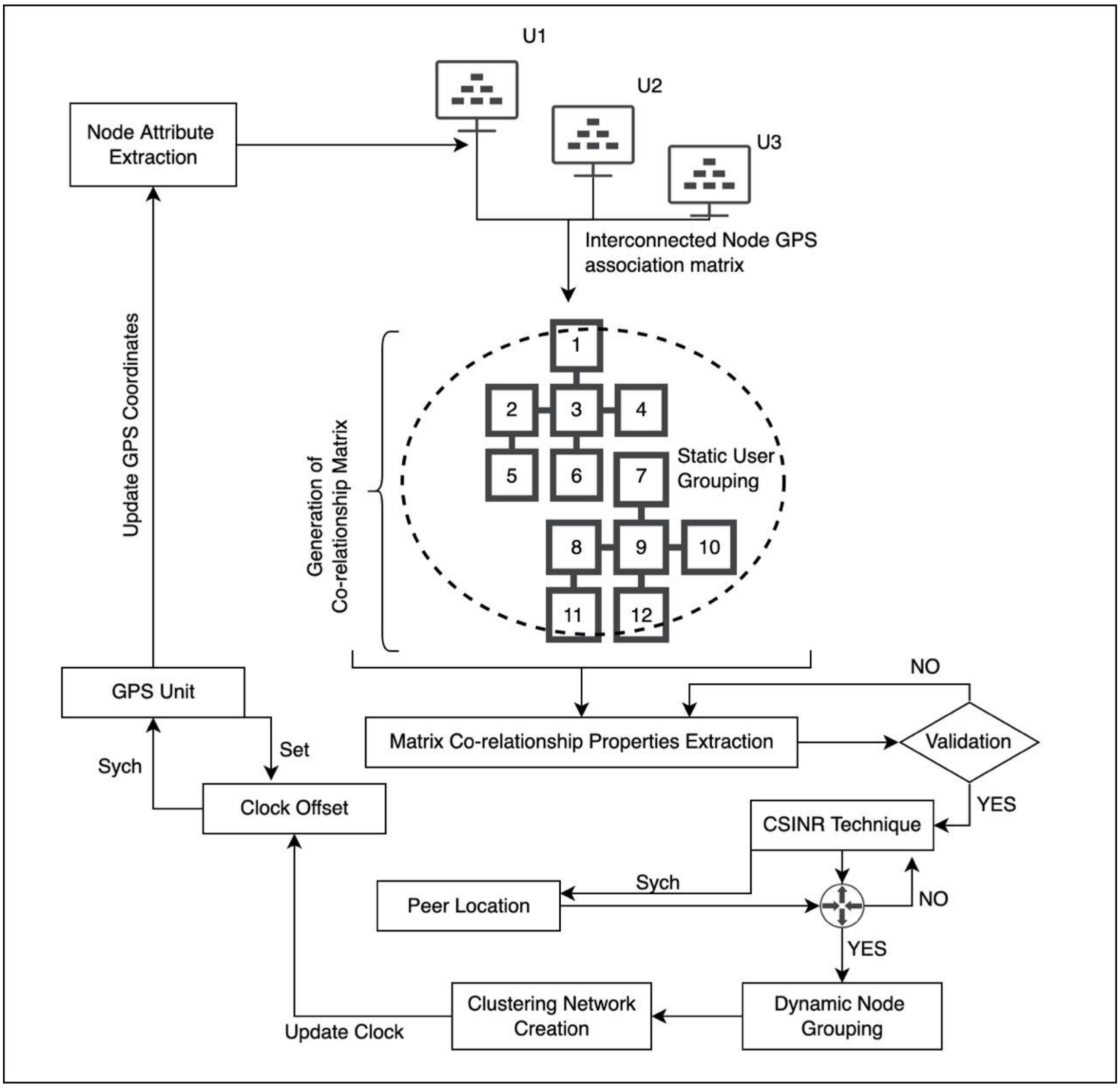

Fig. 1: Block representation of CSINR technique

The primary node attributes are inter-related to NAE based internode association matrix extraction. This matrix is relatively effective as it consists of multiple attribute and association ratio under the network. The Static User Grouping (SUG) is defined and proposed to provide a reliable structure in defining and customizing the node allocation and space relationship for maximizing the performance as shown in Fig. 2. This internally, evaluates node based generation of co-relationship matrix. The process of node categorization provides the framework to fetch an extra mile towards customizing each node activity and label the node based on its approach such as static or dynamic. This results in extraction of inter-dependent matrix of GPS coordinates.

Each extracted and categorized node is classified and processed under a validation process and then appended with Centric Self-Learning Interconnected Nodes Reading (CSINR) with a peer interaction and cluster node creation as shown in Fig. 3. The internal auditing of nodes values $(N_1 \text{ to } N_n)$ under each categorized matrix (Y_i) is customized and clustered. The cluster data is typically bonded and processed with a summation matrix for node synchronization. This involves a defecated clock pre-set and offset coordinates of given GPS location acting as threshold. The (f_o) features on each inter-dependent matrix of attributes from Fig. 2 represents the static approach to analyze and validate the node's existing value with respect to the reporting agent location. The yielding value of grouping the matrix is shown in Fig. 4, with a novel zone based categorization where each R_X and Z_X represents the dependency values of inner zone and outer zone respectively.

The spatial representation is represented in three-dimension model to assure the clear understandability of CSINR technique under each nodes GPS tracking and reporting. On the process of node extraction, the inner zone *(Z_X)* is customizing the nodes as static nodes and thus computes the values, whereas the outer zone *(R_X)* is categorizing the nodes as dynamic nodes. Since the nodes are shifting at the threshold boundary, the extracting parameters are limited and hence, the ratio of projecting observation curve is maximized. Each cluster *(c)* is a relatively responsible for node capturing and classification. This assures the nodes are updated in multiple entries and exit.

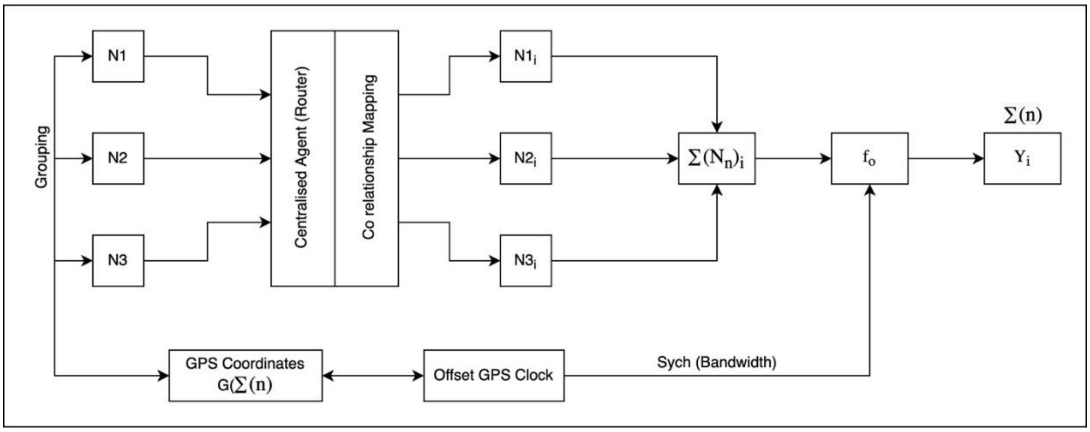

Fig. 2: CSINR Technique based static user grouping

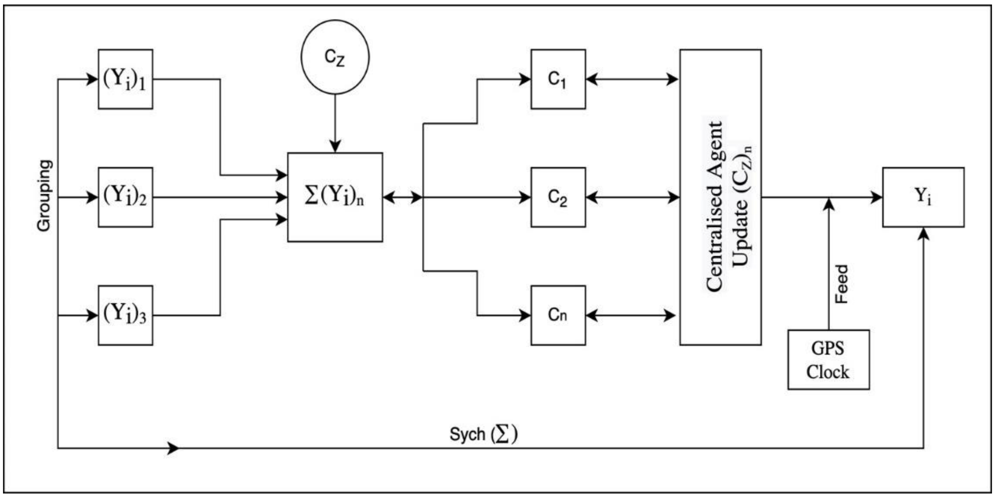

Fig.3: CSINR Technique based on dynamic user grouping and self-learning

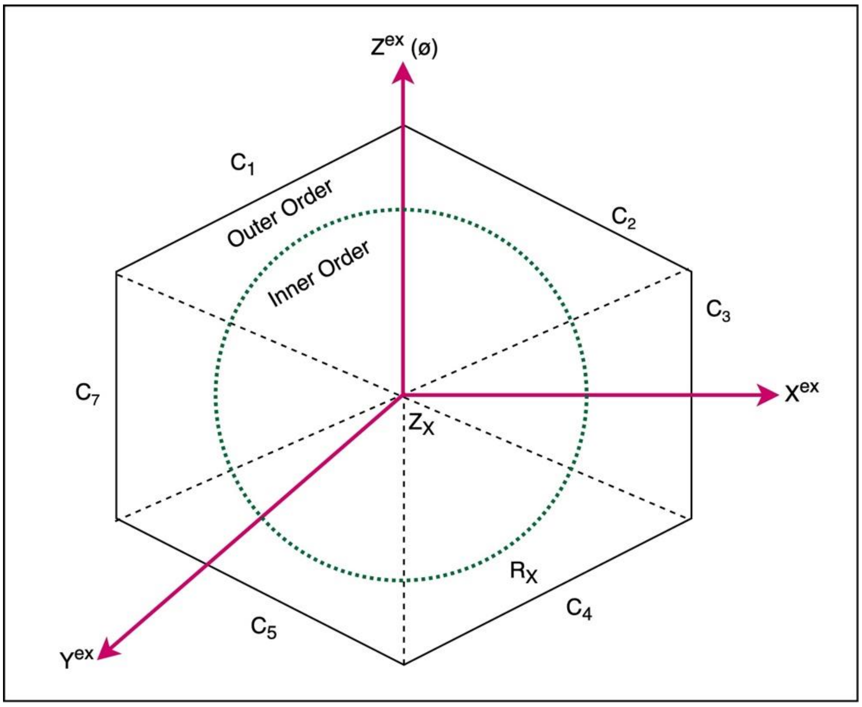

Fig. 4: CSINR Spatial Representation

IV. Mathematical Model

The formulation of a hexagonal orbit and networking circuit is a challenging task as the coordination and occurrence of GPS tracking is based on interconnected nodes approach. Hence, consideration of multi-factor values and dimensions are to be evaluated. Typically, the GPS factor of a given device is considered as $G = \{G_1, G_2, G_3 \ldots G_n\}$ with each factor of GPS is authenticated to centralized database/server $\{D_n\}$ such that $\{G_i \Rightarrow D_n\}$ under an order of $[r,s,t]^i$ where *'r'* is a receiver, *'s'* is a sender and *'t'* is a reliable bit of transmitting values. Typically, the represented is as below

$$\{D_n\} = (P_i + G_i) \Rightarrow \left(\mathrm{P}_i + [r,s,t]^{G_i}\right) \tag{1}$$

$$\therefore D_S = \left(\sqrt{\left(\sum_{i=0}^{\infty} D_{S\,i}\right)}\right) - \Delta G \tag{2}$$

Where ΔG is the optimized value of GPS coordinates supported and aligned with $\{D_S\}$ and incoming GPS values *(G)* as $\{G \subseteq \Delta G\}$ with reference to $\{D_S \Rightarrow\} L(\Delta G)$ where *'L'* is the location of ΔG and dependency. Technically, the order of location (L) with a supporting factor of $[r,s,t]^i$ is represented as below.

$$r = \sqrt{(r - r_i)^2 + (r - r_{i+1})^2 + (r - r_{i+2})^2 + \ldots\ldots} \tag{3}$$

$$S = \frac{1}{\sqrt{r\left(r-r_i\right)^2}}\overrightarrow{\Delta G} \tag{4}$$

$$t = \sum_{i=0}^{\infty}\left(r_i \to \left(\sum_{j=0}^{n} \Delta L_i \frac{\Delta G_j}{\partial t} \right)\right) \tag{5}$$

Boundary Value Fixing and Categorization

The each independent parameter of information shared within the give $\left[r,s,t\right]^i$ zone is validated and factorized. The incoming factor *(I_f)* shall be considered for evaluating the GPS coordinates. The space coordination of each signal value is represented as in Eq. 6 and Fig. 4 respectively.

$$\left[I_f\right] = \left| \begin{matrix} \cos\theta^{\dagger}\sin\varphi & \left(\sin\theta^{\dagger}\cos\varphi+\sin\varphi\cos\theta^{\dagger}\right) \\ -\left(\cos\theta^{\dagger}\sin\varphi\right) & \left(-\sin\theta^{\dagger}\cos\varphi-\sin\varphi\cos\theta^{\dagger}\right) \\ \sin\varphi & -\sin\theta+\cos\varphi \end{matrix} \right. \tag{6}$$

The dependency values of each occurrence in these cyclic spaces are evaluated and filtered based on the occurrence event and GPS coordinates alignment. The coordinated $\left[r,s,t\right]^i$ is a factorial value of each node with reference to noise bandwidth as regional values $\left(U_{acc}\right)$ and $\left(U_{inc}\right)$ to reframe an authentic node under the given operation space.

$$\left(U_{acc}\right) = \lim_{n\to\infty}\left(\int_{i=0}^{n}\frac{\delta\left(I_f\right)_i}{\delta t}\right) - \Delta G_i[r,s,t]^i \tag{7}$$

$$\left(U_{inc}\right) = \lim_{n\to\infty}\left(\frac{\Delta G\left[\delta\left(I_f\right)_i\right]}{\delta t} - \sum_{j=0}^{n}\left(\frac{\delta\left(\Delta G_i\right)_j}{\delta t}\oplus\Delta G\right)\right) \tag{8}$$

$$\therefore U = U_{acc}\oplus U_{inc} \tag{9}$$

The summarization of independent factor noises and current values in U_{acc} and U_{inc} is represented in U_i the fundamental parameters of each instance occurrence is fetched with a cross validation of attributes as shown in Eq. 10.

$$\delta U\left(t\right) = \frac{\delta\left(U_{acc}\right)}{\delta t}\oplus\frac{\delta\left(U_{inc}\right)}{\delta t}$$

(10)

$$\delta U(t) = \sum_{i=0}^{\infty}\sum_{j=1}^{n}\left\{\frac{\delta(U_{acc})_i}{\delta t} \oplus \frac{\delta(U_{inc})_j}{\delta t}\right\}$$

(11)

$$\therefore \delta U(t) = \sum_{i=0}^{\infty}\sum_{j=1}^{n}\left\{\frac{\delta(U_{acc})_i \oplus \delta(U_{inc})_j}{\delta t}\right\} \otimes G_i$$

(12)

$$\therefore \overrightarrow{\delta U(t)} = \lim_{n\to\infty}\left(\frac{\Delta G_i[r,s,t]^i}{\Delta \mathrm{T}(0.248)}\Delta G_i\left[\frac{\delta(Ut)}{\delta t}\right]_0^{\infty}\right)$$

(13)

$$\therefore \overrightarrow{U(t)} = \left(\frac{\Delta G_i[r,s,t]^i}{\Delta \mathrm{T}(0.248)}\left\{\lim_{n\to\infty}\left(\sum_{i}^{\infty}\sum_{j}^{n}\left(\frac{\delta U(t)_i}{\delta t} \oplus \frac{\delta\overrightarrow{U(t)}_j}{\delta t}\right)\right)\right\}\right)$$

(14)

$$\therefore \overrightarrow{U(t)} = \left(\frac{\Delta G_i[r,s,t]^i}{\Delta \mathrm{T}}\left\{\lim_{n\to\infty}\left(\sum_{i,j}^{n}\left(\frac{\delta U(t)_i \oplus \delta\overrightarrow{U(t)}_j}{\delta t}\right)\Delta G_i\right)\right\}\right)$$

(15)

Where $\delta U_i \Rightarrow \delta U(t)$ represents the fundamental values of GPS coordinators of users (U) under a given environment of ΔG. These coordinates are further implemented using a rational computation from existing user labels U_{acc} and neighbor node U_{inc}. These nodes are inter-connected and matrix of nearest GPS accuracy is evaluated and processed. The GPS environment variable shown in Eq. 9 demonstrates the dependency as shown in Eq. 16

$$e(t) \Rightarrow \delta\left(eU_{acc} \oplus eU_{inc}\right)^{\mathrm{T}}$$

(16)

Where, eU_{acc} and eU_{inc} are the environmental variable that are associated to the node or user space (T) with $(\forall \mathrm{T} \subseteq \Delta G)$ and $(\Delta G \in eU)$ as each (U) users is associated with nearest node values in the defined environment of operation.

Self-Learning Module for GPS coordination

The fundamental environment of user operation $\left(\vec{U}\right)$ under the operation principle of $\left(\delta U \Rightarrow \delta\left(\overrightarrow{U(t)}\right)\right)$ the self-learning approach reflects the orbit and space of operation through which the defined user is under authentic operations. Consider the self-learning parameter (S_P) under the influence of environment *(e)* variable as $\left(S_P \in e^{\mathrm{T}}\right)$ where *'T'* is the higher order of user space provided within the environment space. The nodes (n) with an attribute correlation are as $S_P = \left[(n_i)_1, (n_i)_2, (n_i)_3 \ldots (n_i)_n\right]$ such that $\left(\forall S(n_i) \Rightarrow \forall e^{\mathrm{T}}\right)$ with a supporting variable of independent feature.

As per the Eq. 15 and Eq. 16, the fundamentals of users $\left(\delta(u)\right)$ location attribution is equated with an independent factor values $\left(V_f\right)$ such that each of $\left(V_f\right) \Rightarrow \forall e^{\mathrm{T}}$ in user U_{acc} and U_{inc} is matched. The matrix of user representation under self-learning is demonstrated in Eq. 17 respectively.

$$S_P = \begin{cases} \left(\dfrac{\delta\left(U_{acc} \oplus U_{inc}\right)}{\delta t}\right) \otimes \Delta G_i \\ \left(\dfrac{\delta\left(U_{acc} \oplus U_{inc}\right)}{\delta t}\right) \otimes \left[\left(V_f\right)_i\right]_0^n \end{cases} \tag{17}$$

$$\therefore S_P = \begin{cases} \left(\dfrac{\delta\left(U_{acc} \oplus U_{inc}\right)}{\delta t}\right) \otimes \left[r, s, t\right]^{\mathrm{T}} \Delta G_i \\ \left(\dfrac{\delta\left(U_{acc} \oplus U_{inc}\right)}{\delta t}\right) \otimes \sum_{i=0}^{n} \left[\left(V_f\right)_i\right] \Delta G_i \end{cases} \tag{18}$$

The dependency factor of multiple values attributes in User U_{acc} and U_{inc} is dependent on $\left[r, s, t\right]^{\mathrm{T}}$ factor, the initial setup order to extract and develop a factorial value with respect to $\left[\Delta G_i\right]$ where $\left[\forall G \subseteq \Delta G_i \cup \Delta L_i\right]$ provides each location bound is fractional and dependent to users location coordinates. Consider location $\left[\Delta L\right]$ breakout as shown in Eq. 19 respectively.

$$\left[L\right] = \left(\frac{\delta\left(U_{acc} \oplus U_{inc}\right)}{\delta t}\right) \cong \left(\frac{\delta(r)^{e\mathrm{T}}}{\delta t} - 0.728\Delta\mathrm{T}\right) \tag{19}$$

$$[\Delta L] = \left(\frac{\delta \left(U_{acc} \oplus U_{inc} \right)}{\delta t} \right) \cong \left(\sum_{i=0}^{n} \frac{\delta \left(r \right)^{eT}}{\delta t} - 0.728 \Delta \mathrm{T} \right) \tag{20}$$

The learning paradigm of multi-feature with respect to location and orientation of it is equated in Eq. 20. The fundamental contribution of self-learning framework is to achieve a reliable source of GPA coordinates. The process is parallel to the contribution of uses to user interaction as shown in Eq. 19 and Eq. 20 respectively. Hence, the orientation of information mapping in the GPS neighboring nodes is monitored and recorded. Typically, the recording process includes a simulated ecosystem of node_name identification and location extraction. This reflects the shortlisting of information sources into the order of evaluation. The line of scope *(I)* is evaluated to cross validate the attribute occurrence and precision mapping.

V. Results and Discussions

The proposed technique has achieved a higher order user grouping using the current location of GPS coordinates as demonstrated in previous section, the evaluation approach of information collection and user classification is processed and updated. A detailed validation of comparative evaluation is reported in Fig. 5, the diagram is compared with the proposed (CSINR) technique with the existing labeling technique. The major difference of either technique is with respect to the node representation and location freezing.

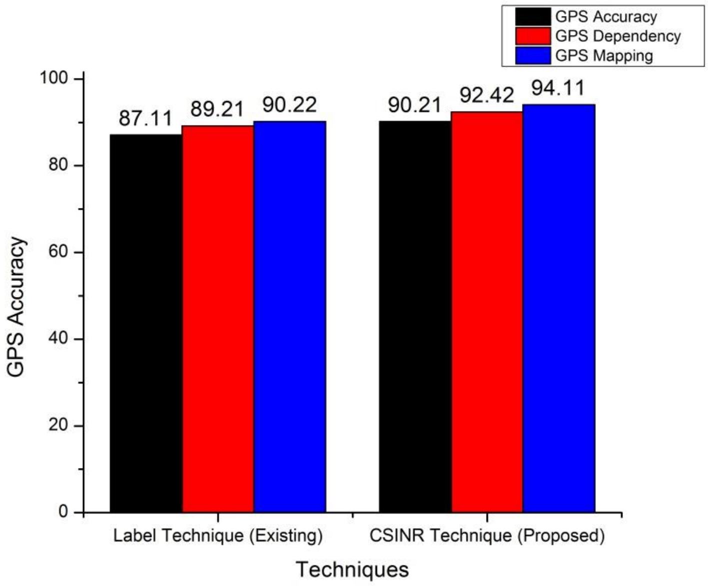

Fig. 5: GPS parameters validation and evaluation

The Fig. 5 demonstrates the performance and accuracy of GPS prediction and labeling of its location in the operating medium. The proposed CSINR technique has demonstrated a reliable solution for given experimental setup. Table.1 is a supporting paradigm of proposed system enhancement with reference to existing system and approaches such as Plotting, labeled technique and recommendation technique. The overall projection in GPS strength and GPS values have an improved performance ratio compared to the existing technique. The projection curve for providing a reliable GPS prediction is improved compared to the plotting and labeled technique, whereas the system is relatively constant with recommendation technique and proposed (CSINR) technique. Fig. 6 demonstrates the

Table-1: Comparative validation of proposed

	Plotting Technique	**Labeled Technique**	**Recommendation Technique**	**CSINR Technique**
GPS Strength (Hz)	2.863	2.8921	2.911	2.9342
Labeled Values (%)	87.21	88.23	92.24	94.92
GPS Values (Arbb)	81.86	92.01	90.42	97.62
Minimal Distance (m)	3.27	4.11	4.21	4.89
Variable Distance (m)	0.45	0.45	0.5	0.9
Projection Curve (m)	3.71	3.88	3.91	3.91

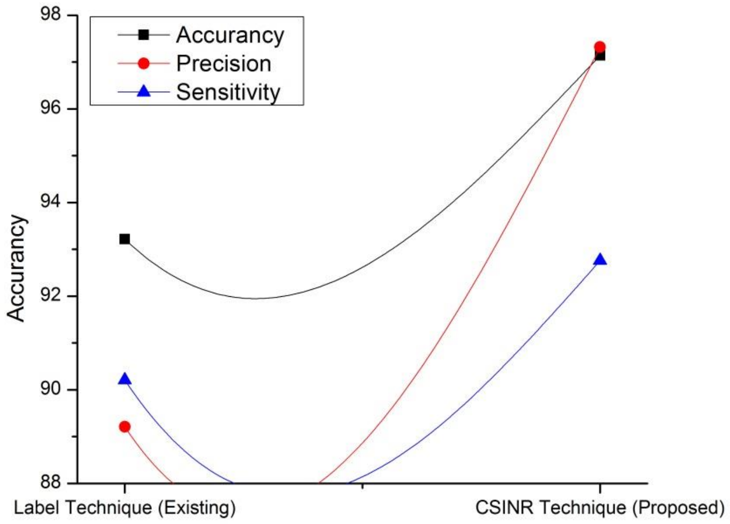

Fig.6: Outcome validation of proposed technique

The proposed technique (CSINR) is further computed and evaluated under the matrix of TEC based notation, the matrix of delay computation and SNR ratio is evaluated as shown in Fig. 7 and Fig.8 respectively. The performance of communication under GPS coordinates mapping is synchronized with an accuracy of 97.32% with proposed CSINR technique as shown in Fig. 9

Table 2: Comparative Matrix of CSINR v/s TEC

Nodes	**TEC-Delay (ms)**	**CSINR-Delay (ms)**	**TEC (SNR)**	**CSINR -(SNR)**	**TEC (Accuracy %)**	**CSINR (Accuracy %)**
4	23.76	21.54	44.21	43.21	88.32	93.21
8	33.97	32.91	48.21	47.21	89.3	93.92

16	42.09	39.21	49.32	47.29	90.31	94.03
32	47.01	43.11	53.32	48.32	90.94	94.72
64	50.32	48.21	55.82	49.43	91.43	97.32

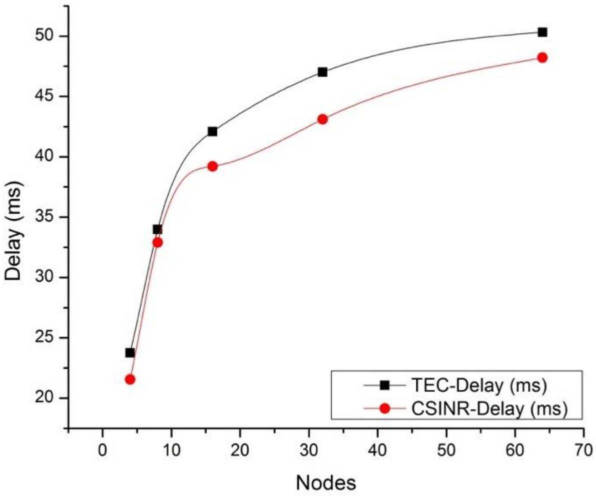

Fig. 7: Time Delay computation of TEC v/s CSINR

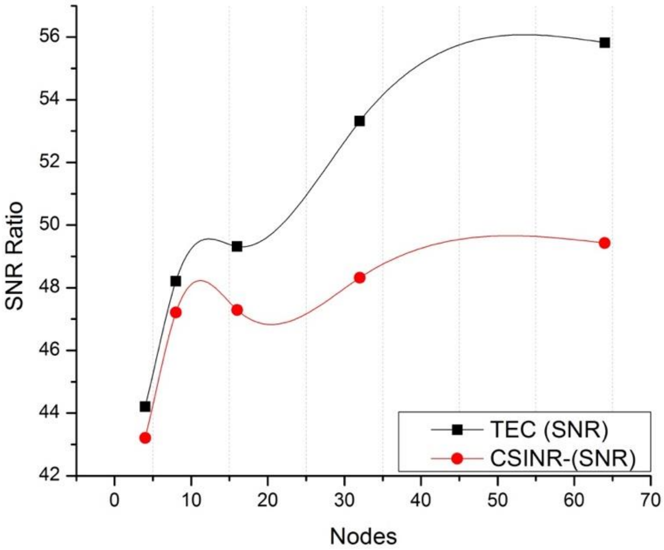

Fig. 8: SNR ratio computation of TEC v/s CSINR

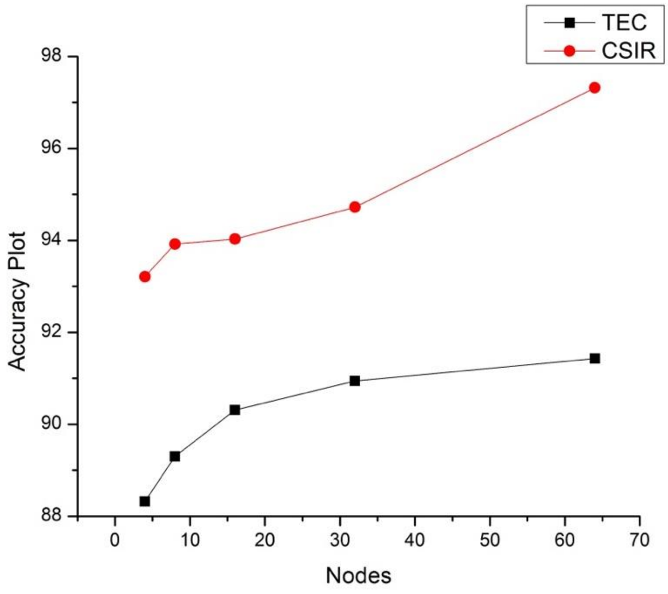

Fig. 9: Accuracy Computation of TEC v/s CSINR

VI. Conclusion

The proposed technique aims to design and develop a dedicated and most reliable approach for GPS accuracy tracking and mapping. The proposed technique has been developed on MATLAB2016 under networking and signal processing tool box. The technique has achieved a higher order of accuracy with a novel centric self-Learning Interconnected Node Reading (CSINR) technique over the improvised schematic representation of Total Electron Content (TEC). This technique is developed on attribute based location extraction and inter-connected co-relationship mapping. The coordination matrix produces a pseudo hexagonal networking ecosystem for reliable communication. The dedicated space of operation plays a major role by customizing the needs and attributes of dynamic user/nodes. The technique has proved the dependency and precision mapping using self-learning module of GPS coordination. The overall proposed technique has demonstrated a result of 97.32% in precision of GPS mapping and marking with 96.82% of accuracy inter-domain GPS coordinated extraction. The technique has overall achieved 97.14% accuracy in communication via dynamic node environment. In near future, the technique can be implemented on dynamic user categorization and grouping.

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