SAR IMAGE RECONSTRUCTION METHOD OF INCOMPLETE RAW DATA BASED ON MATRIX COMPLETION

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Abstract. This paper discusses a new approach of SAR image reconstruction based on matrix completion from afew number of samples of the received SAR signal required by the Nyquist theorem in both the azimuthand range. The reconstruction method has goal to fill the missing information in the raw data caused byunder sampling based on matrix completion of Fourier coefficients. Experiments were performed on the simulated point target and the real RADARSAT1data in noise freeand noisy condition. Compared with the conventional method as range doppler algorithm, the proposed method presented slightly better results in suppressing of side lobe and canmaintain resolution SAR imagery, but with the advantage with a few number of measurements. Asexpected, the larger the number of measurements, a target SAR image can be reconstructed rarelybetter. The experiments on the RADARSAT1data showed the almost same performance as in thesimulation on the target points.

Keywords: SAR, compressive sensing, matrix completion, filling missing, Radarsat-1

1. Introduction

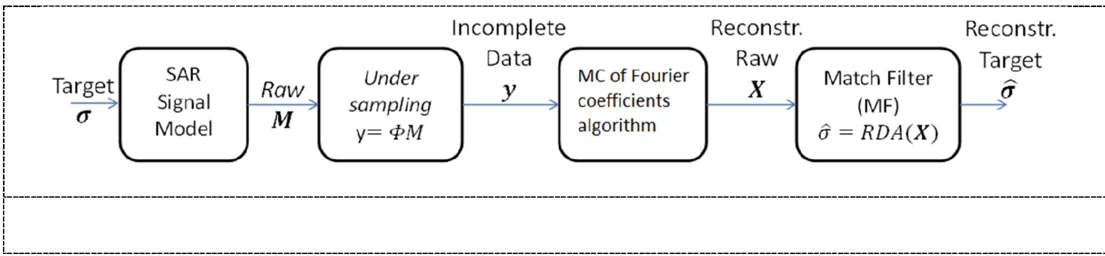
SAR technology has an ability to generate high resolution and wide swath image data. The huge amount of image data is handled in limited onboard storage capabilities and transmission lines. Compressed sensing (CS) (Candes et al. 2006; Candes 2008; Candes et al. 2006; Donoho 2006; Baraniuk et al. 2007; Wei et al. 2010) provides ability to reduce the energy by decreasing the transmitted signal randomly and can recover specific radar signal by solving the linear optimization problem from fewer number of sampling than required under Nyquist/Shannon theorem. In other words, the high rate ADC on conventional system can be replaced with the low rate ADC. So that the volume of image data that contains SAR signal becomes smaller, and the existing power and onboard components of a radar system still can be used or even reduced.

Many CS methods on the SAR data have been proposed in recent years. Of all the research is divided into two groups of the implementation scheme(a) the reconstruction model SAR image from sparse representation and (b) SAR raw data reconstruction model based matrix completion.Sparse representation model of SAR imaging consists of modeling the target sparse, modeling SAR data acquisition in the form of linear equations, modeling the low sampling and reconstruction algorithm CS. The schemes of this model proposed by (Baraniuk et al. 2007; Wei et al. 2010; Herman et al. 2009; Huan et al. 2011) which states that the radar system with CS can eliminate the need of match filter on the radar receiver and reduce the sampling rate conversion process analog to digital in the receiver and can reduce sidelobes drastically.Besides the advantages already mentioned, there is a major problem in this model that produces a large measurement matrix, which causes a very intensive matrix calculation. The second SAR raw data reconstruction model is a method of SAR image reconstruction based on matrix completion (Yang et al. 2014; Arief et al. 2013; Zhang et al. 2010; Sun et al. 2014) by filling the corrupted raw data caused by under sampling or noise. The reconstruction process is performed to fill in the missing data with a value close to the original raw data and the SAR image formation from the raw data using match filter (MF), such as range doppler algorithm (RDA)

(Cumming et al. 2005; Wang 2008). On the research (Yang et al. 2014), the SAR raw data are undersampled in the corresponding azimuth cells, (Arief et al. 2013) only in range cell. This paper discusses a SAR image reconstruction based on matrix completion of Fourier coefficientsfrom afew number of samples of the received SAR signal in both the azimuthand range simultanously.

2. SAR image reconstruction using matrix completion

In this section describes the proposed method of SAR imaging based on matrix completion of Fourier coefficients to recover the raw data from the fewer number sampling entries of slow time and fast time radar signal. Henceforth the above is called MC-RDA and is described in the below diagram in Figure 1. The proposed method is compared to the conventional method RDA (Cumming et al 2005; Wang 2008).



2.1 SAR signal model

Energy source hits an object as incident field and it causes the radiation scattering from the object called scattered field. The incident field has a pulsed LFM radar transmitted waveform and can be written as follows:

$$\mathcal{E}^{in}(t,x) = \mathrm{G_a}.\mathrm{a(t)}.\mathrm{e}^{\mathrm{i}(\omega_o(t)+\pi\alpha(t)^2)} \quad (1)$$

Where $\mathrm{G_a}$ is the amplitude of the transmitter signal and $\mathrm{a(t)} = \mathrm{rect}\big((t-T_p/2)/T_p\big)$ is a rectangular gate function with T_p as the pulse duration time. The $\omega_o = 2\pi f_c$ is the carrief frequency and LFM pulse chirp rate.When an incident field has contact to the object, it will induce currents hence the object emits the scattered field which is the same signal, but weaker and time delayed. The scattered field $\mathcal{E}^{sc}(t,x)$ is formed from the interaction between the target and the incident field $\mathcal{E}^{in}(t,x)$. Thus its value is the response target depends on the geometry and material properties of the target and of the shape. The equation of scattered signal can be written as follows:

$$\mathcal{E}^{sc}(t,x) = -\iint \frac{\delta(t-|x-z|/c)}{4\pi|x-z|} V(z) \frac{\partial^2}{\partial t^2}\Big(\mathcal{E}^{in}(t',z) + \mathcal{E}^{sc}(t',z)\Big)\, dtdz \quad (2)$$

The equation (2) is integral Lippman-Schwinger equation which shows that $\mathcal{E}^{sc}$ depends on the total electrical field$\mathcal{E}^{tot}(t',z) = \mathcal{E}^{in}(t',z) + \mathcal{E}^{sc}(t',z)$. The equation becomes non linear, because $\mathcal{E}^{sc}$exist on both sides of the equation. This has consequences that $\mathcal{E}^{sc}$becomes complex to be resolved.

For radar imaging, the scattered field can be measured at the antenna and the reflectivity V(z) is a function that must be resolved. By the non-linear equation on(2)the reflectivity function will be hard to be solved. Thus, Born approximation (weak scattering approximation) is applied to approach the solution. $\mathcal{E}^{sc}$ is assumed to be much weaker than the incident field $\mathcal{E}^{in}$ ($\mathcal{E}^{sc} \ll \mathcal{E}^{in}$). So that $\mathcal{E}^{tot}$ on the right side of the equation is replaced by$\mathcal{E}^{in}$ in ($\mathcal{E}^{in} \approx \mathcal{E}^{tot}$). The new equation of scattered field in time and frequency domain can be derived as:

$$\mathcal{E}_B^{sc}(t,x) = -\iint \frac{\delta(t-|x-z|/c)}{4\pi|x-z|} V(z) \frac{\partial^2}{\partial t^2} \mathcal{E}^{in}(t',z)\, dt\, dz \quad (3)$$

where $t' = |x-z|/c$ is the time of the EM wave needed to cover the distance between the antenna and the target. It is assumed a monostatic case, where the position of the transmitting antenna x and receiving antenna y (x=y) are in one platform and the distance between the target position z from the antenna x. Then scattered field by the receiving antenna is obtained as follows

$$\mathcal{E}^{sc}(t,x) = -\int \frac{{\omega_0}^2}{16\pi^2 R^2} V(z).\, G_a\,.\, a(t).\, e^{i(\omega_o(t-\tau)+\pi\alpha(t-\tau)^2)} dz \quad (4)$$

where $R(z) = |x-z|$ is the distance between the antenna and the target and $\tau = 2R(z)/c$ is the time delay, which is the travel time of chirp signal from the antenna to the target and back to the antenna.

A base band modulated signal can be obtained by eliminating the carrier frequency, followed by a low pass filter through quadrature demodulation process is as follows:

$$\mathcal{E}_B^{sc}(t,x) = -\int \frac{{\omega_0}^2}{16\pi^2 R^2} V(z).\, G_a.\, a(t).\, e^{(-i\omega_o\tau+i\pi\alpha(t-\tau)^2)} dz \quad (5)$$

The above formula applies to the pulse radar system based on stop-go approximation (Franceschetti et al. 1999), which is the transmit signals is sent at an certain antenna position x and time t. In continuum model, radar antenna is usually pointed toward the earth on the moving platform and simultaneously emits radar signals. The antenna path is denoted by indexη_i, which represents antenna position movement path with $\eta_i = 1, \ldots, N$. The time scale on this model is defined into 2 scales, which the time scale on the antenna movement is much slower (slow time) than the time scale on the EM wave of a radar signal (fast time). The received radar signal can be defined as follows:

$$\mathcal{E}_B^{sc}(t,\eta_i) = -\int \frac{{\omega_0}^2}{16\pi^2 {R_{\eta_i k}}^2} V(z).\, G_a.\, a(t).\, e^{\left(-i\omega_o\tau_{\eta_i k}+i\pi\alpha\left(t-\tau_{\eta_i k}\right)^2\right)} dz \quad (6)$$

where $\tau_{\eta_i k} = 2.\, R_{\eta_i k}/c$ is the delay time of SAR echo at index η_i dan $R_{\eta_i k}$ is the distance (range) between the radar antenna at the position η_i and each target at the position z (x_k, y_k). The distance is formulated as follow

$$R_{\eta_i k} = \sqrt{(\eta_i^2 - y_k^2) + (h^2 + (X_c + x_k)^2)} \quad (7)$$

where h is height of the radar sensor and X_c is the range center to target.

The reflectivity V(z)of the radar illuminated target is formed using the range Doppler algorithm (RDA) by correlating the obtained noisy raw SAR signal with template reflections from ideal radar scattering.

2.2 Measurement Algorithm

We denote a data matrix with sampled entries that are corrupted with noise in form of

$$y = \Phi(x+z) \quad (8)$$

Where Φ is a under sampling measurement matrix, $x \in \mathbb{R}^{n_1 \times n_2}$ is the noiseless data matrix and $z \in \mathbb{R}^{n_1 \times n_2}$is noise matrix. The noise can be stochastic or deterministic. The matrix M contains here only m of the total entries $n_1 \times n_2$ are known, which means undersampling ratio $r = m/(n_1 \times n_2)$.Based on the available samples, the missing values can be recovered to get the reconstructed matrix $X \in \mathbb{R}^{n_1 \times n_2}$ as shown in (Candes et al. 2008) on the case that the matrix has a low rank characteristic.

Aunder sampling model in form of fewer random measurements is needed to reduce the SAR raw data. It represent incomplete matrix. The number of measurements m must be at least smaller than the signal/image dimensions$m \ll (n_1 \times n_2)$. There are 4 types of sampling techniques on the raw data SAR to form measurement matrixin time domain as shown in Figure2(a) full sampling, where all the received signal are sampled required by Nyquist criteria(b) under sampling of slow time (azimuth) signal by random arrangements of transmitted radar pulses (Yang et al. 2014; Liu et al. 2011) (c) under sampling of fast time (range) signal by using lower rate ADC than received signal (Arief et al. 2013; Sun et al. 2014) and (d) undersampling of both slow time and fast time signal simultaneously

(Xu et al. 2012). Black dots in the image shows the sampled signals, so that the number of white dots indicating the fewer number of measurements taken, or the higher the compression ratio.

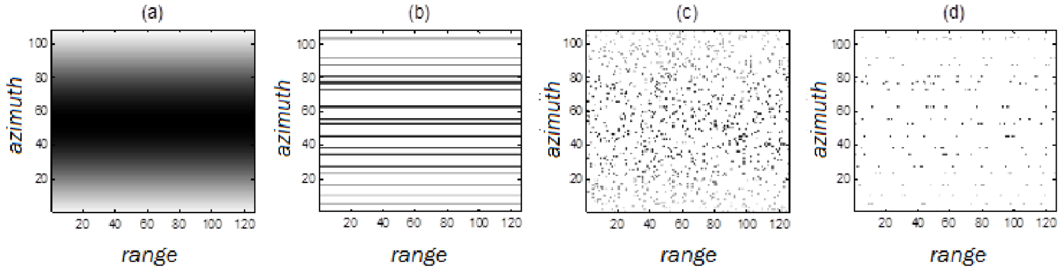


Figure 2. Sampling techniques of SAR signal (a) fullsampling (b) undersampling of slow time signal (c) undersampling of fast time signal and (d) undersampling of both slow time and fast time signal

2.3 Matrix completion of Fourier coefficients.

Due to under sampling, data transmission errors or acquisition errors, some samples of a signal aremissing. The missing samples must be filled in with suitable values. The samples or pixels should be convincingly filled in according to the surrounding area. In this case, the problem of fillling in missing samples/pixelsis often called inpainting. In this section, we will describe a SAR image reconstruction method based on matrix completion of Fourier coefficients

We assume x is a radar signal (6) of length N. But suppose only K samples of slow time and fast time signal as are observedof in Figure 2d, where K< N. The M-point incomplete signal y can be written as

$$y = \Phi x \qquad (9)$$

where Φ is a sampling matrix of size $K \times N$. The signal y consists of the known samples of x. Suppose the signal x has a sparse representation with respect to A in frequency domain, meaning that x can be represented as

$$x = \mathrm{A}\mathrm{c} \qquad (10)$$

where c is a sparse coefficient vector of length N with $M \leq N$, and A is a sparse representation matrix of size $M \times N$. The coefficients c are frequency domain (Fourier) coefficients. Then the incomplete signal y can be written as

$$y = \Phi \mathrm{A}\mathrm{c} \qquad (11)$$

The problem can be stated to find the Fourier coefficients c from the incomplete signal y and the matrix Φ.Any vector c satisfying from (3) can be considered a valid set of coefficients. To find a particular solution we can minimize c by solving the least square solution (Candes et al. 2008).

$$\underset{c}{\operatorname{argmin}} \|c\|_2^2 \text{such that } y = \Phi \mathrm{A}\mathrm{c} \qquad (12)$$

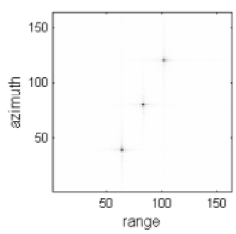
Then we can find an estimate $\hat{x}$ of x by setting

$$\hat{x} = \mathrm{A}\mathrm{c} \qquad (13)$$

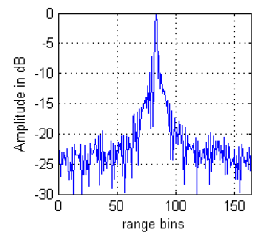
3. Result and discussion

As demonstration of the performance of proposed imaging algorithm on SAR data we provide raw data from point scattered target and a complex scene of a ship from Radarsat-1 image. The SAR image was formed from full sampled raw data using RDA. Otherwise, both SAR raw data areunder sampled in azimuth and range direction simultaneously with 20% and 50% random samples.The reconstructed images of both targets from fewer numbers of samples were generated using MC-RDA. The results were compared with the RDA methods to evaluate the performance of the MC-RDAmethod.

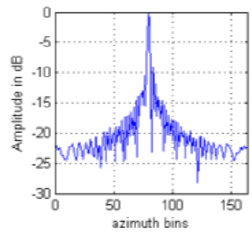
Visually the processed image of the three point target did not show a difference between the two methods in figure 3. It is clear that MC-RDA reconstruction method produces image from the compressive measurements less than 50% random samples of point target not better then the RDA does from the full simulated data.



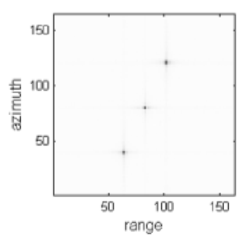
(a) Point image formation from RDA processing



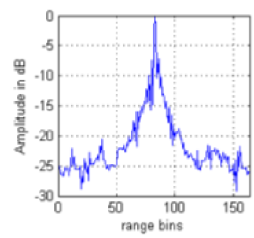
(b) Spectrum of point spread in range from RDA processing



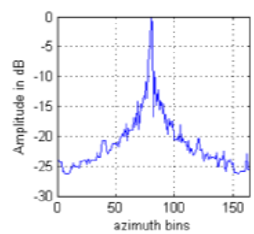
(c) Spectrum of point spread in azimuth from RDA processing



(d) Point image formation from MC-RDA processing



(e) Spectrum of point spread in range from MC-RDA processing



(f) Spectrum of point spread in azimuth from MC-RDA processing

Figure 3. RDA and MC based SAR processing of point targets and the spectrum of point spread function in range and azimuth

The PSLR and ISLR of the reconstructed point targets are 10,4196 dB dan -15,423dB in azimuth direction using RDA (see table 1).

Table 1. SAR quality parameter in 3dB resolution, PSLR and ISLR of point targets

	Azimuth			Range		
	3dB Res. [pixel]	PSLR [dB]	ISLR	3dB Res. [pixel]	PSLR [dB]	ISLR
RDA	1,750694	-10,4196	-15,423	2,199166	-7,20096	-11,9706
CS 50%	1,787203	-10,7587	-15,3122	2,211913	-7,44063	-12,1435
CS 20%	1,809340	-10.0945	-15.9805	2,35366	-7,29780	-12,0442

Figure 4 shows imaging results of RDA and MC method applied to some real Radarsat1 data. The scatering of the sea can be ignored, because it is too weak compared to scatering of the ships. The imaging results of the presented MC method using 20% and 50% echo samples. The performance of MC assessed based on the number of measurements. The results show that the larger the amount of measurement of echo samples, the more scattering point can be reconstructed.

(a) (b) (c)

Figure 4. The SAR imaging results of a ship (a) RDA image (b) MC RDA 20% samples and (c) MC based RDA 50% samples

4. Conclusion

Under-sampling technique is done by reducing the number of measurement samples of both fast time and slow timeradar signals randomly simultaneously. The under sampling formed on two time scales (1) under sampling of slow time signal by shipping arrangements of radar pulses randomly. (2) under sampling of fast time signal by a reducing the sampling rate of ADC under Nyquist criteria.This sampling method shows a decrease in the number of samples significantly and also the volume of raw datacan be dramatically reduced.

Compared with the traditional RDA, MC-RDA method may present relative the same results in suppressing of side lobe and can maintain resolution SAR imagery. We find that the performance of CS recovery algorithms depends on the number of measurement and the input SNR. The larger the number of measurement samples, with a target SAR image can be reconstructed rarely better.SAR image quality results show that the proposed MC–RDA method was better than the RDA method at high SNR.

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GLOBAL NAVIGATION SATELLITE SYSTEM IN THAILAND

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Abstract. GNSS has played an important role for navigation system also monitoring environmental for many years. The GNSS network around the world has about 500 stations. Thailand has 3 stations across the country from North to South. However, other stations that operate by Thai government (Thai Meteorological Department-TMD, Royal Thai Survey Department-RTSD, Department of Lands-DOL, and Department of Public Works and Town & Country Planning-DPT) are almost 30 stations. The use of GNSS in Thailand currently tends to be increasedparticularly in transportation navigator and in the business for find the solution to the customer.

1. Introduction

Global Navigation Satellite System (GNSS) is the data of positioning and timing. It collects ground control points for aerial triangulation and obtain the direct observation of the exterior orientation. Currently, almost 500 stations have been installed around the world but only few stations in some country such as Thailand, India have 3 stations, whileCambodia, Myanmar, Egypt or Laos have no any station (Figure 1).

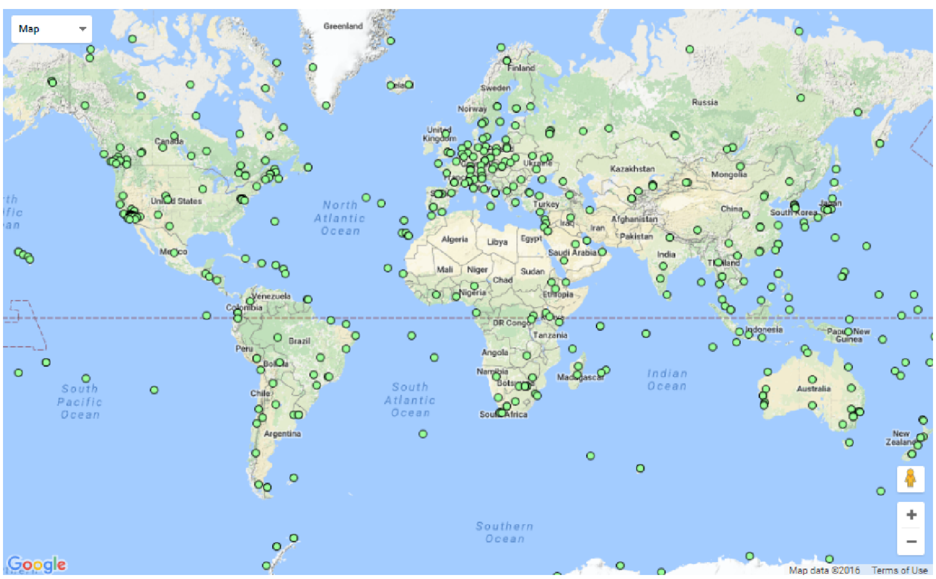

Figure 1. Stations location around the world. Source: International GNSS Service (2016)

The International GNSS Service (IGS) is the international organization that has different type of data such as parameter of earth's rotation, global ionosphere maps, information of satellite and tracking station clock, GNSS satellite ephemerides. Therefore, researcher around the world could download and use these data as Awange (2012) has reviewed the applications of GNSS i.e. for environmental monitoring, environmental impact assessment or environmental pollution or Khodabandeh and Teunissen (2016) used to determine total electron content (TEC), and Nadarajah et al. (2014) and Giorgi et al. (2012)used for attitude determination and positioning for direct geo-referencing.The software to operate these data is RTKLIB that is an open source program package for GNSS positioning. The first version (0.2.0) was launched on 16 December 2006 and now the newest version (2.4.3) was released on 31 March 2015 (Takasu, 2015).

2. GNSS in Thailand

According to IGS (2016), there are 3 stations that were installed in Thailand;North, Central and South (Figure 2). Station CMUM is located in the North, Chiang Mai Province, CUUT is in Bangkok, Central and the south has CPNM station at Chumphon Province (Table 1). For each station photo and detials can be seen in Figure 3 and Table 1.

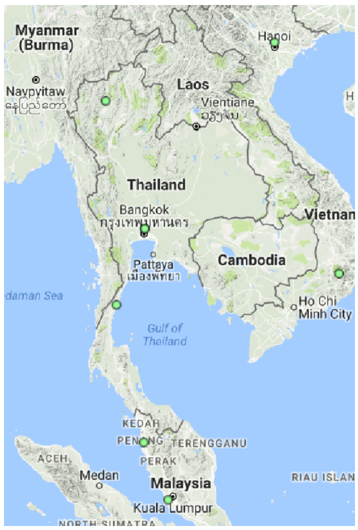

Figure 2. Three stations that operation by JAXA Edit from International GNSS Service (2016)

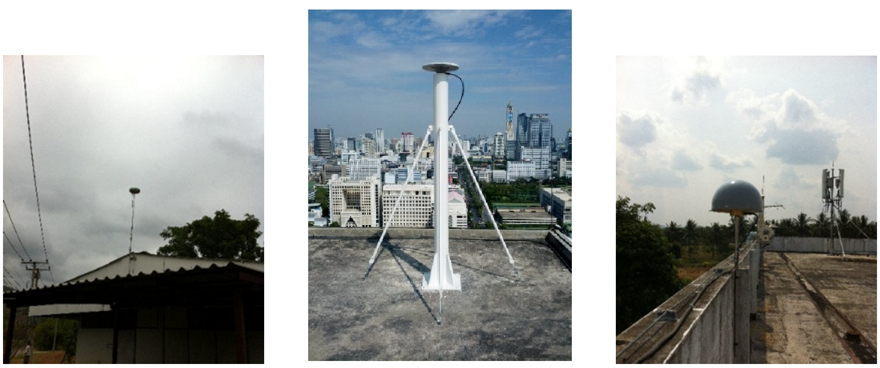

Figure 3. Photo of three stations in Thailand (left: CMUM, middle: CUUT, right: CPNM. Source: International GNSS Service (2016)

Table 1. Details of all three stations in Thailand

Station	Latitude	Longitude	Elevation (meter ellips)	Install date	Province	Site name
CMUM	184539.15N	0985556.56E	308.962	18 Feb 2014	Chiang Mai	Chiang Mai
CUUT	134409.56N	1003202.16E	74.296	13 Jan 2015	Bangkok	Chulalongkorn University
CPNM	104328.74N	0992227.76E	9.143	4 Apr 2013	Chumphon	Chumphon

Source: International GNSS Service (2016)

Several of Thai government departments have involved with GNSS data such as Department of Public Works and Town & Country Planning (DPT), Thai Meteorological Department (TMD), Royal Thai Survey Department (RTSD), Department of Lands (DOL), for the first who has the Real Time Kinematic in Thailand is DOL (Rizos and Satirapod, 2011).

The Ionospheric and GNSS data center which is operated by King Mongkut's Institute of Technology Ladkrabang (KMITL), is set to monitor Ionospheric and the efforts to create a GNSS and Ionospheric database in Thailand. Therefore, there are approximately 30 stations around Thailand that some stations collect only Ionospheric data such as PTC station (Phuket) or some stations collect GNSS data such as KMIT (Bangkok), CIMU (Chiang Mai University) or PTAC (Phuket) (Ionospheric and GNSS Data Center, 2016).

As it can be seen in Figure 4, there are about 30 stations over Thailand with different department of operation, as DPT has 11 stations across country, while DOL mainly has station around middle of Thailand or TMD has no station in the south of Thailand.

The examples of application of GNSS in Thailand are Narupiti (2011) delivery his talk in the United Nations meeting in Japan, about the using GNSS for vehicle tracking, probe vehicle, road management that are operated by ITS Thailand (Transport Systems in Thailand), Arunpold et al.(2012) study the effect of Ionospheric in positioning by using GNSS data in Thailand.

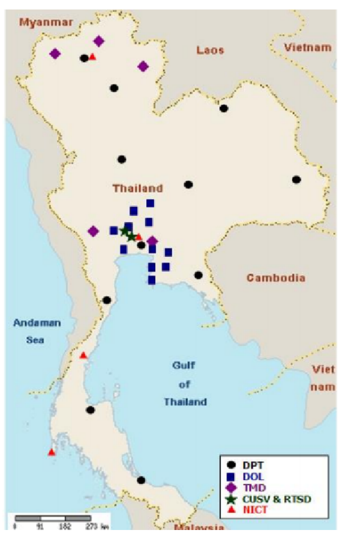

Figure 4. All stations network in Thailand Source: Rizos and Satirapod (2011)

The recent event that related with GNSS in Thailand is the Startup Thailand on 28 April to 1 May 2016 at Queen Sirikit National Conventiion Center, Bangkok. The startup Thailand is the event that has a goal to integrate all organizations (government and non-government) for movement, development and ecosystem support in Thailand. In addition, one of the topic to discuss is "GNSS Technology Opportunity for Thai Startup" and the key note speech are Mr. Deok Jae Choi (Korea

Aerospace Industries), Mr. Rod MacLeod (NovAtel, Canada), Mr. Dave Durey (Lockheed Martin, USA), Mr. Hugh Vanijrabha (Rolls-Royce, Thailand), Mr. Shan Kuo Yang (National Space Organization, Taiwan), Mr. Thierry Gardet (Airbus, France). The key of this discussion is the use of GNSS for transportation navigator especially for aircraft, also in the navigation business in term of find the answer and solution to the customer.

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