# TERRAIN SIGNATURE BASED NAVIGATION

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### ABSTRACT

**In this paper, we propose an alternative solution for long range high resolution navigation that may work independently from global positioning system (GPS) networks. Earth terrain signatures are obtained from satellite images and indexed into an on board memory. It is possible to find to location of an arbitrary terrain by comparing its signature to the pre-recorded terrain signatures of the database.**

## I. INTRODUCTION

An alternative solution for long range high resolution navigation is introduced in this paper. This system does not require any information from the global positioning system (GPS) networks. The terrain signatures are computed from satellite images, and indexed into a signature database. This type of signature indexing is proposed for sound signals [1-5]. Recently there has been some interest in expanding this system for two dimensional data [6-7].

It is possible to navigate with an imaging system, if there is an on board memory with pre-recorded terrain signatures. The real-time images acquired during the navigation is compared to the signatures of the terrain that reside at the on board memory. The location of the acquired image can be identified using the proposed system. Therefore navigation becomes possible without any dependency to the GPS network.

Earth terrain signature obtained from satellite images are processed and indexed into an on board memory. Compass and altitude measurements construct patterns that are used to extract location in a process that works over indexed signature database. Having exact surface reference points that are independent from any network, the system can provide higher sampling rates. Low cost MEMS based INS may become applicable for navigation incorporated cruise control. Since there is no need for any network references, jammer shielding and RF noise immunity problems disappear. This is especially important for military applications. Since the comparison is performed over signature data, there is no need for high performance computational devices.

## II. METHOD

We propose to form a signature database from a large satellite image as shown in figure 1. The first step is to segment the satellite image into smaller terrains. The size of these terrains and the overlap between these terrains are important parameters of the system. Small terrains with large overlaps generate too many entries in the signature database, and these terrains share very similar characteristics. On the other hand, large terrains with little or no overlap decrease the robustness of the system against translation and rotation. They also increase the uncertainty of the location determination problem. Therefore, the terrain segmentation is an important step that affects the overall performance of the proposed system.

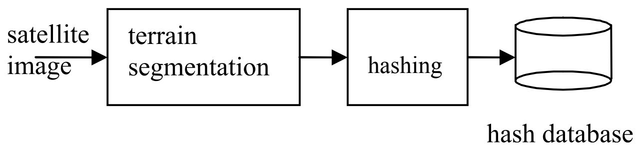


Figure 1: Generation of hash database from a large satellite image

The next step is the hashing process that generates the terrain signature. This hashing function should be robust against translation and rotation of the terrain. In this paper, we propose to use a frequency domain hashing algorithm. In this algorithm, the Fourier transform of the terrain is computed using Fast Fourier Transform (FFT). Let $FFT(.)$ denotes the FFT operation,

$$\mathrm{F}(\mathrm{r},\theta) = \mathrm{FFT}(\ f(x,y)\ ) \tag{1}$$

where f(x,y) is the pixel value of the terrain at location (x,y), and F(r,θ) is the Fourier domain representation of the terrain image in polar coordinates. We then compute the energy within the predetermined rings of the FFT representation as follows:

$$\mu_i = \int_0^{2\pi} \int_{r_{i-1}}^{r_i} | F(r,\theta) |^2 r dr d\theta \qquad (2)$$

where $0<r_{i-1}<r_i<2\Pi$, and $r_0=0$. In addition, we want these features to be independent of the imaging system and the weather conditions. Therefore, we normalize them with the total energy of the image. The $i^{th}$ element of the signature then becomes

$$\beta_i = \frac{\mu_i}{\sum_{i=1}^{R} \mu_i} \qquad (3)$$

where R is the total number of frequency bands that we have chosen. Then the hash vector is form as

$$\beta = [\beta_1, \beta_2, \ldots, \beta_R]^T \qquad (4)$$

where the superscript T denotes transpose. This hashing algorithm is demonstrated in figure 2. The image shown in figure 2(a) is a new terrain image. Its FFT magnitude is shown in figure 2(b) (for better visualization, the logarithm of FFT magnitude is shown), and figure 2(c) demonstrates the frequency rings that we used to compute the signature elements. Our signature elements are the energy distribution of the new terrain in frequency domain within each ring shown in figure 2(c). Note that, the circular integration in this hashing algorithm makes the signatures robust against image rotations.

a)

b)

c)

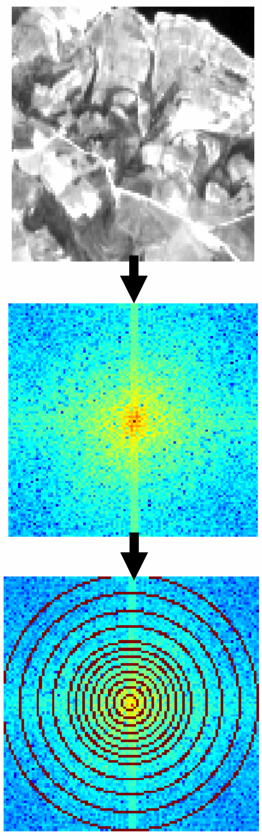

Figure 2: (a) New terrain for location identification, (b) The logarithm of the Fourier transform magnitude of the terrain, (c) The rings used for signature generation.

Once the signatures are computed and recorded for all terrain segments, a signature database is created. The problem is to find the location of a given arbitrary terrain. This terrain may be a translated or rotated version of a terrain that is imaged at another resolution. The difference in the resolution may be caused by the resolution of the imaging system, weather conditions, and the altitude of imaging. To find the location of the given terrain, it has to be adjusted for the resolution for proper signature generation. After resolution adjustment and hashing, the obtained signature is compared to the values that are in the signature database. For this comparison, a metric is required. A simple quadratic metric can be used for this purpose. Let $\beta_{new}$ denote the signature of the given terrain, and $\beta_k$ denote the signature of the $k^{th}$ terrain that is stored in the signature database. The index of the matched terrain from the database is estimated as follows:

$$index = \arg\min_k (\beta_{new} - \beta_k)^T W (\beta_{new} - \beta_k) \qquad (5)$$

where W is a diagonal weighting matrix for this quadratic distance metric. Since the location of each terrain in the database is known, we can determine the coordinates of the given terrain from this estimated index. The signature of the new terrain is compared to the pre-recorded signatures that are in the signature database. The distance between the signatures of the given terrain and the matching terrain should be minimal. The overall algorithm for finding the location of an arbitrary terrain is shown in figure 3.

The key algorithms of the proposed system are the terrain segmentation algorithm, hashing function, and the metric for comparing signatures. These algorithms determine the overall system performance.

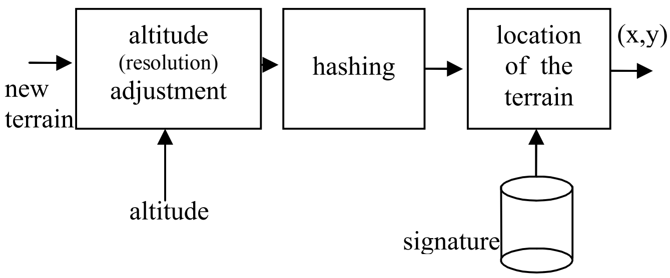


Figure 3: Determining the location of an arbitrary terrain

## III. RESULTS AND DISCUSSION

We implemented the proposed algorithm and tested its performance. We used a satellite image of size 500x3000 pixels that is shown in figure 4. This image is segmented into non-overlapping terrains that are 100x100 pixels. Therefore, there are 150 entries in the signature database.

The resolution of this satellite image is 10 m. Therefore, each of the segmented terrains is 1 km square.

The hashing is applied to a single band of the image. However, it is possible to extend this hashing for multi-band signatures. We selected 12 rings for the computation of energy distribution. The radiuses of these rings are 3, 6, 9, 12, 15, 18, 21, 24, 30, 36, 43, and 50 pixels. Therefore, the signature is formed with the energy distribution within each of these rings, and the length of each signature is 12. The signature database is a matrix of 500x12 entries. In the comparison of the signatures, we did not use any weighting for the frequency bands.

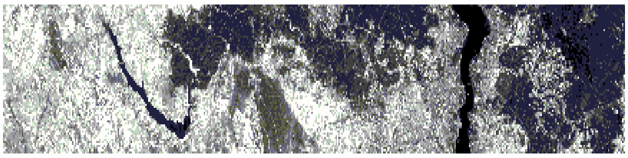

Figure 4: The satellite image used for testing the proposed method

For testing the algorithm, we choose arbitrary terrains from the same satellite image. Therefore, there is no need for resolution adjustment. We prefer not to rotate the image artificially, because the interpolation performed during the rotation affects the spatial information of the image. However we test the algorithm against translation and noise. For noise testing, we used additive Gaussian noise. We took a terrain from the hash database, and add Gaussian noise as

$$f(x,y) = f(x,y) + e(x,y) \qquad (6)$$

where e(x,y) is a Gaussian distributed random variable with zero mean and variance $\sigma^2$. Then we change the variance of the noise and test the performance of the system. There is no translation in the terrain selection. Each terrain in the hash database is tested. A terrain from the signature database is taken and Gaussian noise is added, and then its signature is computed again. The signature obtained from the noisy terrain image is compared to the signatures in the database. The signatures of the database are sorted according to their distance to the given signature of the noisy terrain. We define four different performance measures; top-one success is the case where the minimum distance signature of the database is the correct match. Top-three success is the case where the signature of the noisy terrain has a correct match in the first three signatures that are sorted according to their distance. Top-five and top-ten successes are defined similarly. Figure 5 shows the performance of the proposed algorithm at different noise levels. As it can be seen from this figure, the top one success drops to zero as the variance of the noise goes to 20. Note that, we are using a single band of the satellite image with 8-bit intensity that is scaled from 0 and 255. With top-three success, the proposed algorithm performed 50% success at variance level of 15. According to the top-ten success criteria, the performance of the proposed algorithm is ~60% at noise variance of 20.

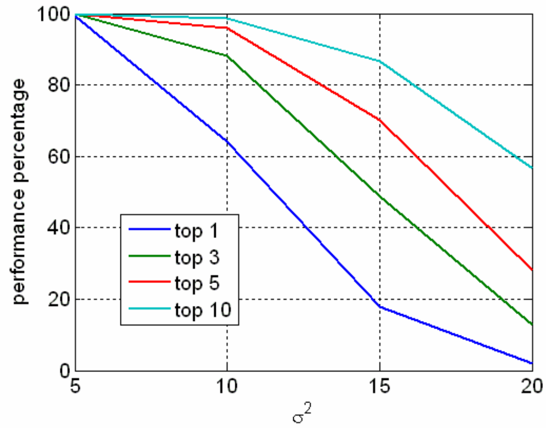


Figure 5: Performance of the system with additive Gaussian noise.

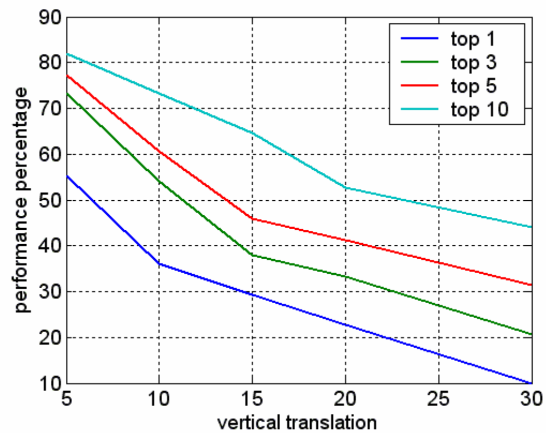


Figure 6: Performance of the system with vertical translation

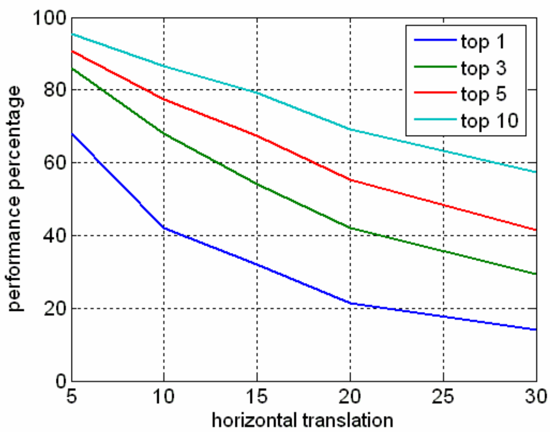


Figure 7: Performance of the system with horizontal translation

We also tested the performance of the proposed algorithm against translation. We picked translated terrains in the vertical and horizontal directions, and try to identify their locations. The performance of the proposed algorithm for vertical translation is shown in figure 6. Similarly, the performance of the algorithm for the horizontal translations is shown in figure 7. From these two figures, we can see that the performance of the algorithm degrades pretty quickly with the translation in both directions. We believe, the proposed algorithm can perform better, if we choose overlapping terrains during segmentation.

## IV. CONCLUSION

In this paper, we showed that it is possible to navigate by using an imaging system and an on board memory of pre-recorded terrain signatures. Our preliminary results show that our implementation of the proposed algorithm needs more features (bigger signature size) for improved robustness against noise. In addition, the terrain should be segmented into terrains that have overlapping regions. This would improve the performance of the proposed algorithm against translation. Therefore, rigorous test are needed to understand the optimum signature size and other system parameters described above.

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