Proceedings of the Applied Imagery Pattern Recognition (AIPR) 2003 Workhop,
Washington, DC, October 15 - 17, 2003.

Registration of Range Data from Unmanned Aerial and Ground Vehicles*

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Abstract

In the research reported in this paper, we propose to overcome the unavailability of Global Positioning System (GPS) using combined information obtained from a scanning LADAR rangefinder on an Unmanned Ground Vehicle (UGV) and a LADAR mounted on an Unmanned Aerial Vehicle (UAV) that flies over the terrain being traversed. The approach to estimate and update the position of the UGV involves registering range data from the two LADARs using a combination of a feature-based registration method and a modified version of the well-known Iterative Closest Point (ICP) algorithm. Registration of range data thus guarantees an estimate of the vehicle's position even when only one of the vehicles has GPS information. Additionally, such registration over time (i.e., from sample to sample), enables position information to be maintained even when both vehicles can no longer maintain GPS contact. The approach has been validated by conducting systematic experiments on complex real-world data.

1. Introduction

With funding from the Army Research Laboratory (ARL) and the Defense Advanced Research Projects Agency (DARPA), the National Institute of Standards and Technology (NIST) is developing architectures and algorithms for unmanned vehicles. The research makes use of the NIST Highly Mobile Multi-Wheeled Vehicle (HMMWV) and an eXperimental Unmanned Vehicle (XUV) developed under the Army's Demo III program [8]. The position estimation for these Unmanned Ground Vehicles (UGVs) relies on fusing Global Positioning System (GPS) reported estimates with other on-board navigation sensors. The required accuracy of the GPS estimates cannot be guaranteed for the entirety of a particular mission as the direct line of sight to the satellites cannot be maintained at all times. GPS can be lost due to multipathing effects and terrain conditions, especially for on-road driving tasks. In order to account for such unavailability and unreliability of GPS, another form of position estimation becomes imperative.

To overcome this problem, the UGV can use aerial survey maps constructed using a downward-looking LADAR (LAser Detection And Ranging) sensor mounted on an Unmanned Aerial Vehicle (UAV). If the LADAR range images from the UGV can be registered to those from the UAV, then these results can serve as secondary position estimates in the event of absence or degradation of GPS. This paper describes a position estimation algorithm that works by registering a scanning LADAR rangefinder on an UGV and a LADAR mounted on an UAV that flies over the terrain being traversed. We propose a hybrid approach which is a combination of both feature-based and point cloud-based Iterative Closest Point (ICP) algorithm for registering two sets of LADAR range images.

The value of aerial imagery obtained via active range sensing for aiding ground vehicle navigation is being recognized within the UGV community. For example, in [11], aerial and ground views from unmanned vehicles are registered by extracting a geometrically consistent set of correspondences using surface signatures from which a registration transformation is estimated. It is not clear, given the computational burden associated with the extraction of surface signatures, whether

∗ Commercial equipment and materials are identified in this paper in order to adequately specify certain procedures. Such identification does not imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

this approach can be implemented in real-time. In [10], an aerial vehicle, a Flying Eye (FE), flies ahead of an UGV acting as a "scout" to detect difficult obstacles from an overhead perspective thus benefitting ground vehicle navigation. The above paper briefly mentions the need for registering the data from the FE to the ground vehicle but the details of the registration process are not presented. The hybrid approach proposed in this paper exploits the simplicity and speed of the iterative closest point algorithm thus lending itself to real-time implementation.

The paper is organized as follows: Section 2 describes registration of 3D LADAR range images using a modified ICP algorithm. Section 3 describes a feature extraction and alignment methodology for accurate registration. Section 4 describes the experimental results. Finally, Section 5 concludes the paper by summarizing the contributions and suggesting further research efforts.

2. Iterative Registration

The iterative algorithm for registering two sets of 3D LADAR data denoted by $\mathbf{M}$ (model) and $\mathbf{D}$ (data) can be summarized by the following steps [2] :

1. For each point in $\mathbf{D}$, compute its closest point in $\mathbf{M}$. This is usually accomplished via 3D nearest point search from the set comprising $N_{\mathbf{D}}$ data and $N_{\mathbf{M}}$ model points.

2. Compute the incremental transformation ($\mathbf{R}$,$\mathbf{T}$) using Singular Value Decomposition (SVD) using correspondences obtained in step **1.**

3. Apply the incremental transformation from step **2.** to $\mathbf{D}$.

4. If relative changes in $\mathbf{R}$ and $\mathbf{T}$ are less than a threshold, terminate. Else go to step **1.**

To deal with spurious points/false matches and to account for occlusions and outliers, the least-squares objective function that is to be minimized is weighted such that [12]:

$$min_{(\mathbf{R},\mathbf{T})} \sum_i w_i \; ||\mathbf{M}_i - (\mathbf{R}\mathbf{D}_i + \mathbf{T})\,||^2 \qquad (1)$$

where $\mathbf{R}$ is a 3×3 rotation matrix, $\mathbf{T}$ is a 3×1 translation vector and the subscript i refers to the corresponding points of the sets $\mathbf{M}$ and $\mathbf{D}$.

If the Euclidean distance between a point x_i in one set and its closest point y_i in the other, denoted by $d_i \stackrel{\triangle}{=} d(x_i, y_i)$, is bigger than the maximum tolerable distance threshold $\mathcal{D}_{max}$, then w_i is set to zero in Equation (1). This means that an x_i cannot be paired with a y_i since the distance between reasonable pairs cannot be very big. The value of $\mathcal{D}_{max}$ is set adaptively in a robust manner by analyzing distance statistics.

Let $\{x_i, y_i, d_i\}$ be the set of original points, the set of closest points and their distances, respectively. The mean and standard deviation of the distances are computed as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} d_i; \quad \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (d_i - \mu)^2}$$

where N is the total number of pairs. The pseudo-code for the adaptive thresholding of the distance $\mathcal{D}_{max}$ is given below:

$$\begin{array}{c}
\texttt{if}\ \mu \ < \ \mathcal{D} \\
\mathcal{D}^{itn}{}_{max} \ = \ \mu \ + 3\sigma; \\
\texttt{elseif}\ \mu \ < \ 3\mathcal{D} \\
\mathcal{D}^{itn}{}_{max} \ = \ \mu \ + 2\sigma; \\
\texttt{elseif}\ \mu \ < \ 6\mathcal{D} \\
\mathcal{D}^{itn}{}_{max} \ = \ \mu \ + \sigma; \\
\texttt{else}\ \mathcal{D}^{itn}{}_{max} \ = \ \epsilon;
\end{array}$$

where itn denotes the iteration number, $\mathcal{D}$ is defined as the average distance between the scan points to be registered and is a function of the resolution of the range data. During implementation, $\mathcal{D}$ was selected based on the following two observations: (i) If $\mathcal{D}$ is too small, then several iterations are required for the algorithm to converge and several good matches will be discarded, and (ii) if $\mathcal{D}$ is too big, then the algorithm may not converge at all since many spurious matches will be included. For more details on the effect and selection of $\mathcal{D}$ and ϵ on the convergence of the algorithm, see [12]. At the end of this step, two corresponding point sets, $\mathbf{P_M}$:$\{\mathbf{p}_i\}$ and $\mathbf{P_D}$:$\{\mathbf{q}_i\}$ are available.

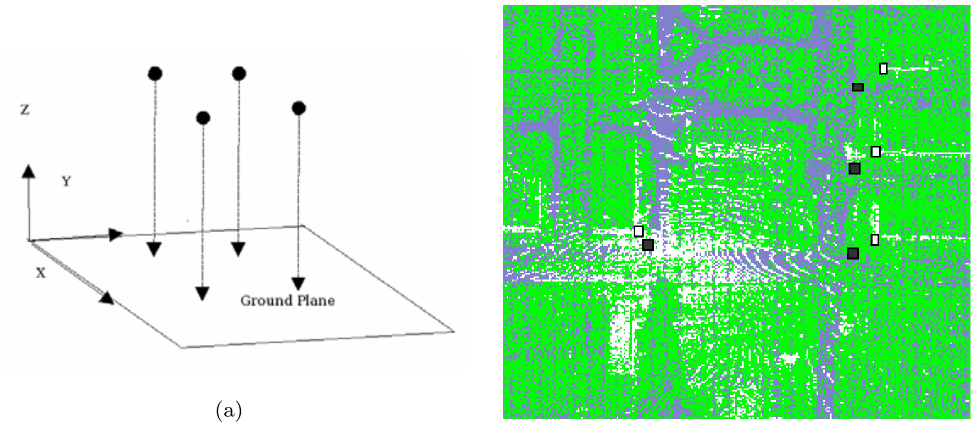
The incremental 3D transformation (rotation and translation) of step **2.** is obtained as follows [1]:

- Calculate $\mathbf{H}$=$\sum_{i=1}^{N_D}(\mathbf{p}_i - \mathbf{p}_c)(\mathbf{q}_i - \mathbf{q}_c)^T$; ($\mathbf{p}_c$,$\mathbf{q}_c$) are the centroids of the point sets ($\mathbf{P_M}$,$\mathbf{P_D}$).
- Find the SVD of $\mathbf{H}$ such that $\mathbf{H} = \mathbf{U}\mathbf{\Omega}\mathbf{V}^T$.
- The rotation matrix relating the two point sets is given by $\mathbf{R} = \mathbf{V}\mathbf{U}^T$.
- The translation between the two point sets is given by $\mathbf{T} = \mathbf{q}_c - \mathbf{R}\mathbf{p}_c$.

This process is iterated as stated in step **4.** until the mean Euclidean distance between the corresponding point sets $\mathbf{P_M}$ and $\mathbf{P_D}$ is less than or equal to a predetermined distance or until a given number of iterations is exceeded. For further details, see [5].

3. Air to Ground Feature-based Registration

The underlying assumption in the iterative registration algorithm is that the rotation angle between the range images that need to be registered is not too large



(a)

(b)

Figure 1. Projection of LADAR data to base ground planes is shown in (a). The extracted features (corners) from the UGV and UAV LADARs are shown as white and black squares, respectively, in (b).

and also that these images are not too far apart. For the current case of UAV and UGV LADAR data, this assumption is overly restrictive and an aiding mechanism for the registration of the range images becomes necessary.

The correspondence determination step is the most difficult and computationally expensive step of the iterative algorithm. Despite the apparent simplicity of this problem, establishing reliable correspondences is extremely difficult as the UGV is subjected to heavy pitching and rolling motion characteristic of travel over undulating terrain. This is further exacerbated by the uncertainty of the location of the sensor platform relative to the global frame of reference. In addition to these factors, noise inherently present in LADAR range images complicates the process of determining reliable correspondences. One solution to overcome the above deficiencies is to extract naturally occurring view-invariant features, for example, corners, from the LADAR scans. Such *control points* can then be used for establishing reliable registration.

Towards guaranteeing robust and accurate registration, we first obtain the z translation value by estimating the ground z values on the UGV and UAV LADAR data in the vicinity of the UGV's current location. For the UGV, the ground values are obtained from the LADAR points that are within a given radius immediately in front of the vehicle and those for the UAV are obtained by finding the minimum of the LADAR values. Then we project the UAV and UGV LADAR data into the base ground planes as depicted in Figure 1(a) and construct the feature planes by using the Canny edge detector [3]. The corner features are detected based on the intersections of lines formed by edges. The corner features are independently extracted from both LADAR data sets by considering those points that are above a given height from the ground as shown in Figure 1(b).

The two sets of the projected corner points (UAV LADAR set: $\mathbf{A}$ and UGV LADAR set: $\mathbf{G}$) are used to estimate a 2D translation. Given two sets of 2D corner points:

$$\mathbf{A} \triangleq \mathbf{a}_j = \begin{bmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{nj} \end{bmatrix};\ j = 1, 2, \cdots n;$$

$$\mathbf{G} \triangleq \mathbf{g}_k = \begin{bmatrix} g_{1k} \\ g_{2k} \\ \vdots \\ g_{nk} \end{bmatrix};\ k = 1, 2, \cdots n;$$

To find a translation along the x and y directions, we first calculate the means of sets $\mathbf{A}$ and $\mathbf{G}$:

$$\bar{\mathbf{a}} = \frac{1}{n}\sum_{j=1}^{n}\mathbf{a}_j; \qquad \bar{\mathbf{g}} = \frac{1}{n}\sum_{k=1}^{n}\mathbf{g}_k;$$

The difference between the means of x, y and that between the aerial and ground z values provide a rough estimate of the required 3D translation between the two sets of LADAR data. The 3D translational offset when applied to the UGV range image enables the ICP algorithm to provide reliable registration results.

4. Experimental Setup and Results

The UAV LADAR produces a 3D point cloud (range image) at up to 6000 pts/sec with a 100 meter scanning range. The UGV is equipped with a long-range 3D Riegl image sensor (LMS-Z420i) which provides 10000 pts/sec with range up to 800 meters. For additional details on the UAV and UGV LADARs, see [6] and [7], respectively. The UAV LADAR provides an aerial survey map with significant information about existing topology and structures.

Figure 2 shows a top view of unregistered LADAR range images obtained from the UGV (in white) and UAV (in black) LADARs, respectively. Figures 3(a)-(d) depict the results of the feature-based registration algorithm. Figure 3(a) shows a top view of the LADAR range images after applying the translation obtained using the corner features. Figure 3(c) shows the results of the iterative registration algorithm applied to the LADAR range images in (a). Figures 3(b) and (d) show a magnified view of stages depicted in Figures 3(a) and (c), respectively. From Figures 2 and 3, it is evident that the LADAR range images are registered.

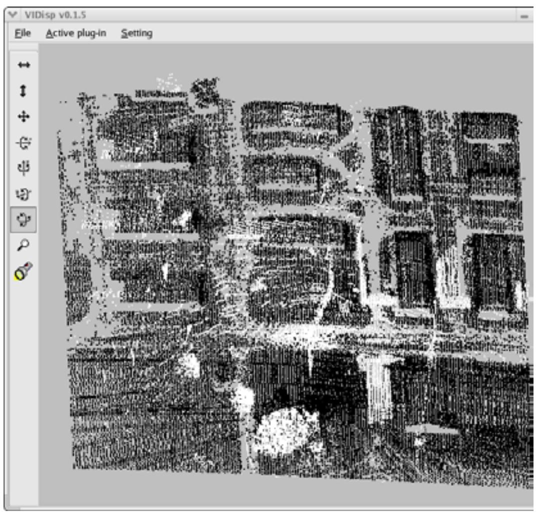


Figure 2. Top view of unregistered range images of UGV and UAV LADARs

A similar sequence of results presented in Figure 4 again shows the efficacy of the proposed feature-based iterative algorithm in registering aerial and ground LADAR range images.

5. Conclusions and Further Research

A hybrid iterative algorithm for registering 3D LADAR range images obtained from unmanned aerial and ground vehicles was proposed in this paper. Combined with a feature-based approach, the algorithm was shown to produce accurate registration for the two sets of LADAR data. Registration of the UGV LADAR to the aerial survey map minimizes the dependency on GPS for position estimation especially when the GPS estimates are unreliable or unavailable. The results presented in the paper demonstrated the potential of this approach lending itself to real-time implementation.

For practical purposes, the LADAR data utilized in this paper can be assumed to be of the same resolution even though typically the aerial data tend to be of lower resolution than that of the UGV LADAR. To address this issue, we are currently developing schemes for use within the ICP algorithm that will inherently account for varying resolution in data sets that need to be registered. Towards this, we are also developing corner detection schemes using the Harris [4] and SUSAN [9] corner detectors.

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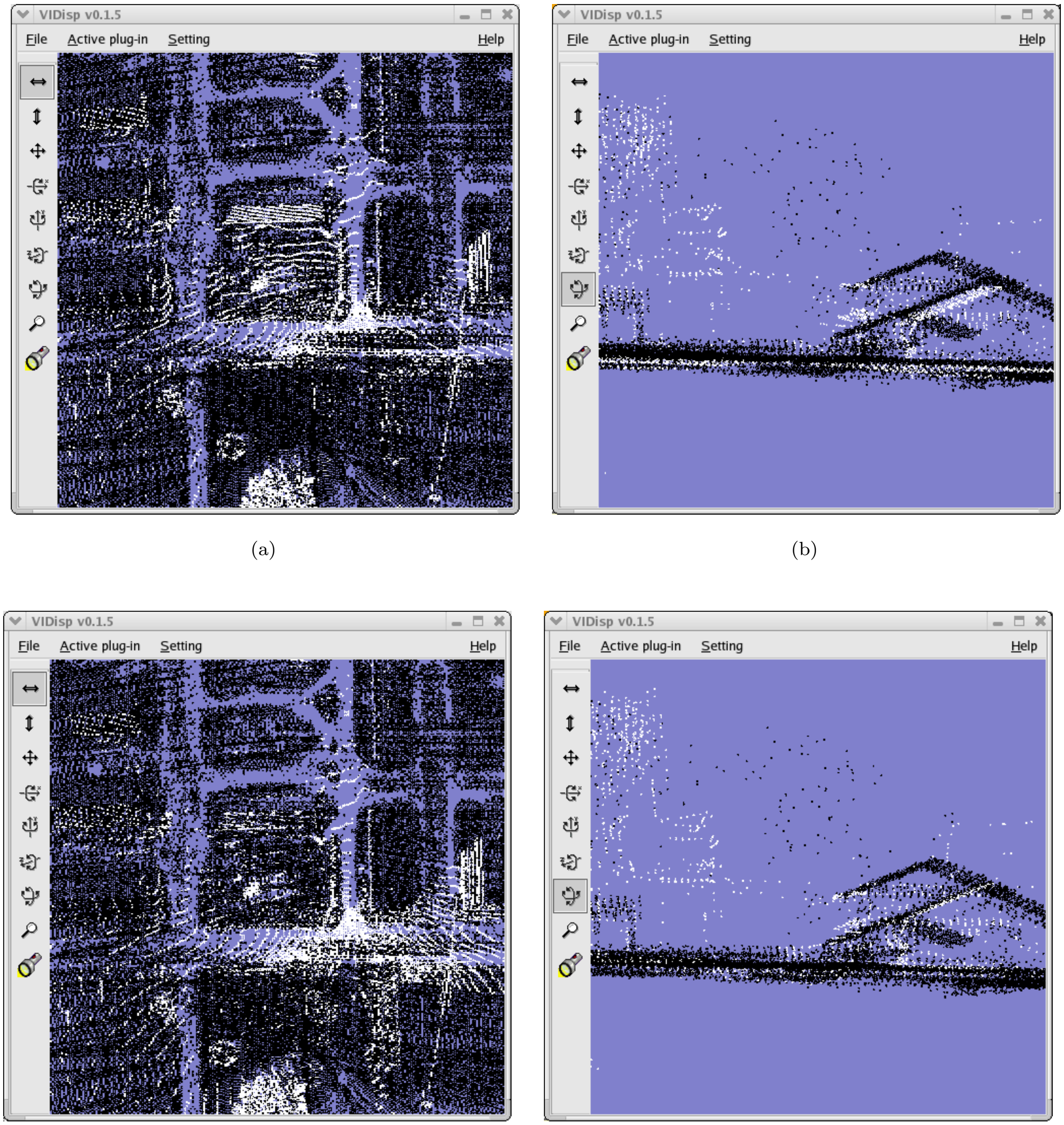

(a) (b) (c) (d)

Figure 3. A top view of the feature-based translation obtained using the extracted corners is shown in (a) and a magnified side view of the same is shown in (b). (c) shows a top view of the registered UAV and UGV LADAR range images obtained by utilizing the feature-based translation results and (d) is a magnified view of (c). See text for further details.

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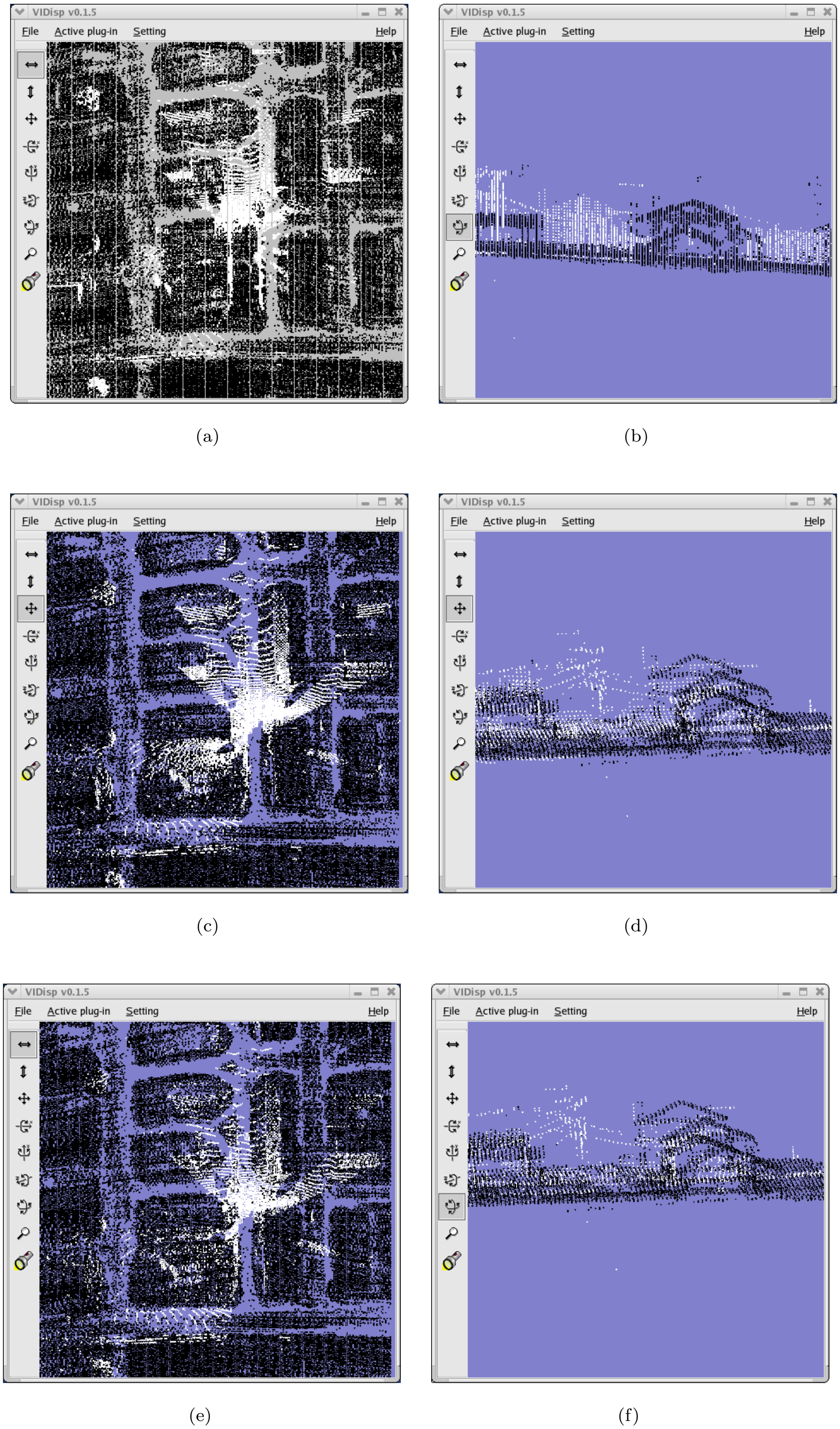

Figure 4. A top view of unregistered range images of UGV and UAV LADARs, the feature-based translation obtained using the extracted corners, and the registered UAV and UGV LADAR range images obtained by utilizing the feature-based translation results are shown in (a), (c) and (e), respectively. (b), (d) and (f), respectively, show magnified side views of their counterparts in the left column.