Visualization and Image Analysis Laboratory

THE ROBOTICS INSTITUTE

Ridge Matching Algorithm Based on Maximal Correlation in Transform Space

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Abstract: Image matching, a common technique in Computer Vision to identify objects, persons, locations, etc., is widely used in both military and civilian applications. Depending on the specific application, different image matching approaches are applied. In the current project, which we call ProbeSight (See Fig.1), the construction of 3D ultrasound models relies on the location data found by matching camera images to a pre-acquired image of the skin [1]. For common image matching algorithms, the precision of the location data can be compromised when changes in ambient lighting conditions affect the camera images. Motivated by the need to reduce the unwanted influence from the ambience, a novel method is proposed to match images that contain features associated with an inherent direction. Since these features often represent real physical structures, they should be consistently captured by the camera under normal variations in ambient light.

Method: Our new method first extracts ridge features in the images, using preprocessing algorithms based on an established scale-invariant ridge detection algorithm [2].

The ridge features are organized into a matrix **S** containing the detected ridge points, each point defined by its orientation (x, y) and location θ (Eq.1). To perform ridge matching, we find the pair-wise rigid transform *t* between every ridge point from one image and every ridge point from another (Eq.2, 3, 4). The result is a point cloud in the Transform Space **K**, defined as the set of all possible transforms (Δx, Δy, $\Delta\theta$).

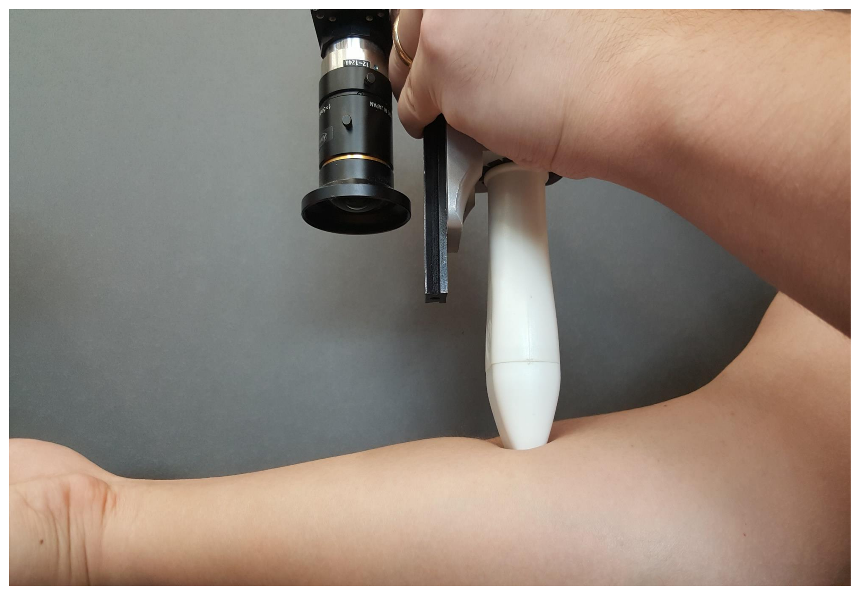


Figure 1 ProbeSight demo. Camera is used to capture the details on the skin. By processing the camera images, this new algorithm helps to calculate the location of the ultrasound probe.

$$\mathbf{S}=\begin{bmatrix} x_1 & y_1 & \theta_1 \\ x_2 & y_2 & \theta_2 \\ \vdots & \vdots & \vdots \\ x_n & y_n & \theta_n \end{bmatrix} \quad s.t\ \mathbf{BW}(x_i,y_i)=1 \quad \text{(Eq. 1)}$$

$$t(v_1,v_2)=(\Delta x,\Delta y,\Delta\theta) \quad \text{(Eq. 2)}$$

$$\Delta\theta=\theta_2-\theta_1 \quad \text{(Eq. 3)}$$

$$\begin{bmatrix}\Delta x\\ \Delta y\end{bmatrix}=\begin{bmatrix}x_1\\ y_1\end{bmatrix}-\begin{bmatrix}cos\Delta\theta & -sin\Delta\theta\\ sin\Delta\theta & cos\Delta\theta\end{bmatrix}\begin{bmatrix}x_2\\ y_2\end{bmatrix} \quad \text{(Eq. 4)}$$

The correlation between two sets of ridge point is equivalent to the density of the point cloud, computed by convolving the point cloud with a blurring kernel (Eq.5). The best match is found as the location in transform space at which the correlation reaches global maximum.

$$D=\left[\sum_{v_i\in S_1}\sum_{v_j\in S_2}\delta\left(\Delta x-\Delta x(v_i,v_j)\right)\delta\left(\Delta y-y(v_i,v_j)\right)\delta\left(\Delta\theta-\Delta\theta(v_i,v_j)\right)\right]*f(\Delta x,\Delta y,\Delta\theta) \quad \text{(Eq. 5)}$$

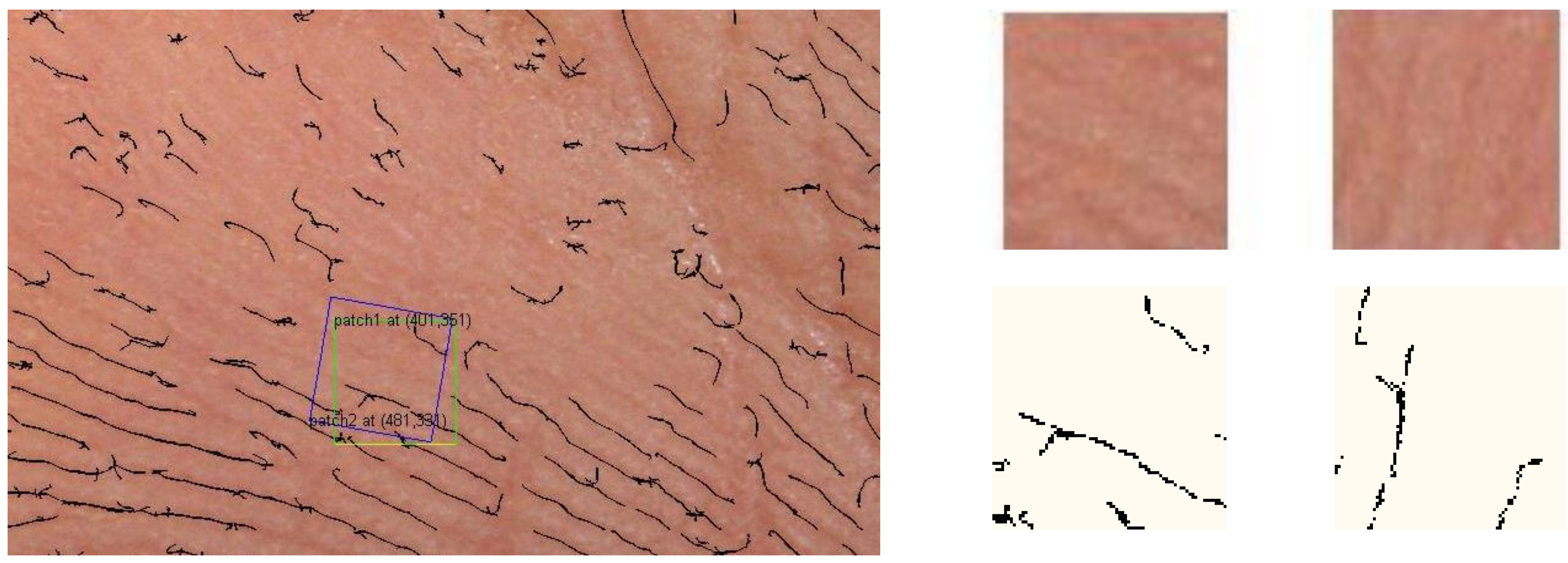


Figure 2a(Left) High resolution map of the human palm where detected ridge points are shown in black. Small sample patches inside the blue box and the green box simulate what the probe mounted camera can see. 2b (Top Right) Raw image samples used to test the new ridge matching algorithm. 2c (Bottom Right) Ridge points detected from the raw samples shown

Results: We tested the algorithm on a pair of images (Fig. 2) sampled from a high resolution image at known locations and known angles. The translational offsets are (80, -20) and the rotation between them is 80 degrees.

After all the transforms were found, the point cloud in Fig. 3 was generated. No maximum density is evident in the figure because overlapping points obscure each other. To find the maximum density, we convolved the point cloud with the blurring kernel *f* to obtain the density map *D* (Fig. 4a, 4b). The density map *D* shows a prominent global peak that ocurrs at (80, -19, 80°), accurate to a single pixel, given sampling error.

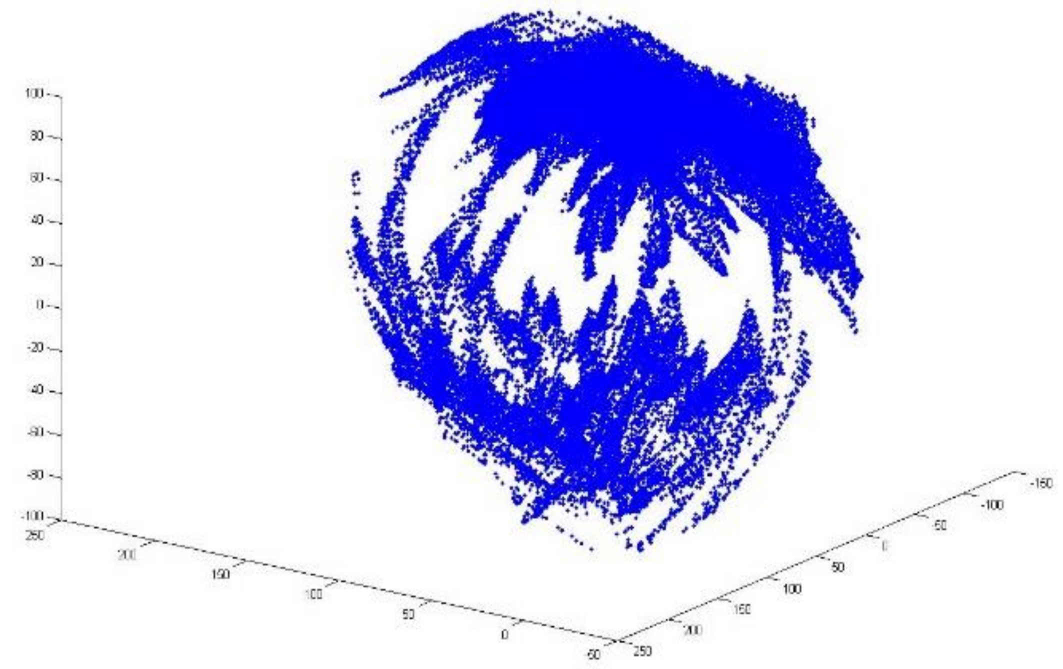
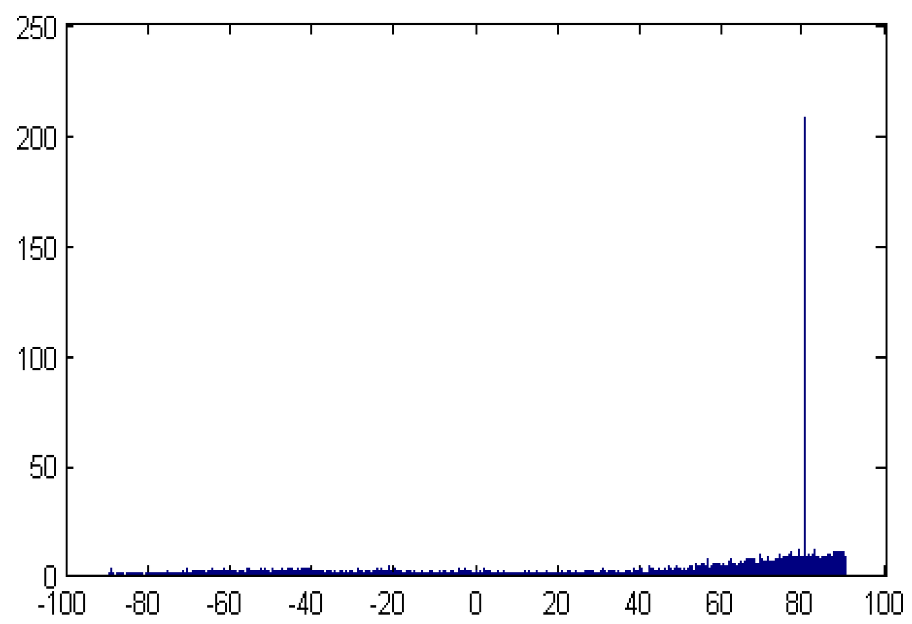


Figure 3 Point cloud in the Transform Space K. The vertical axis represents rotation Δθ



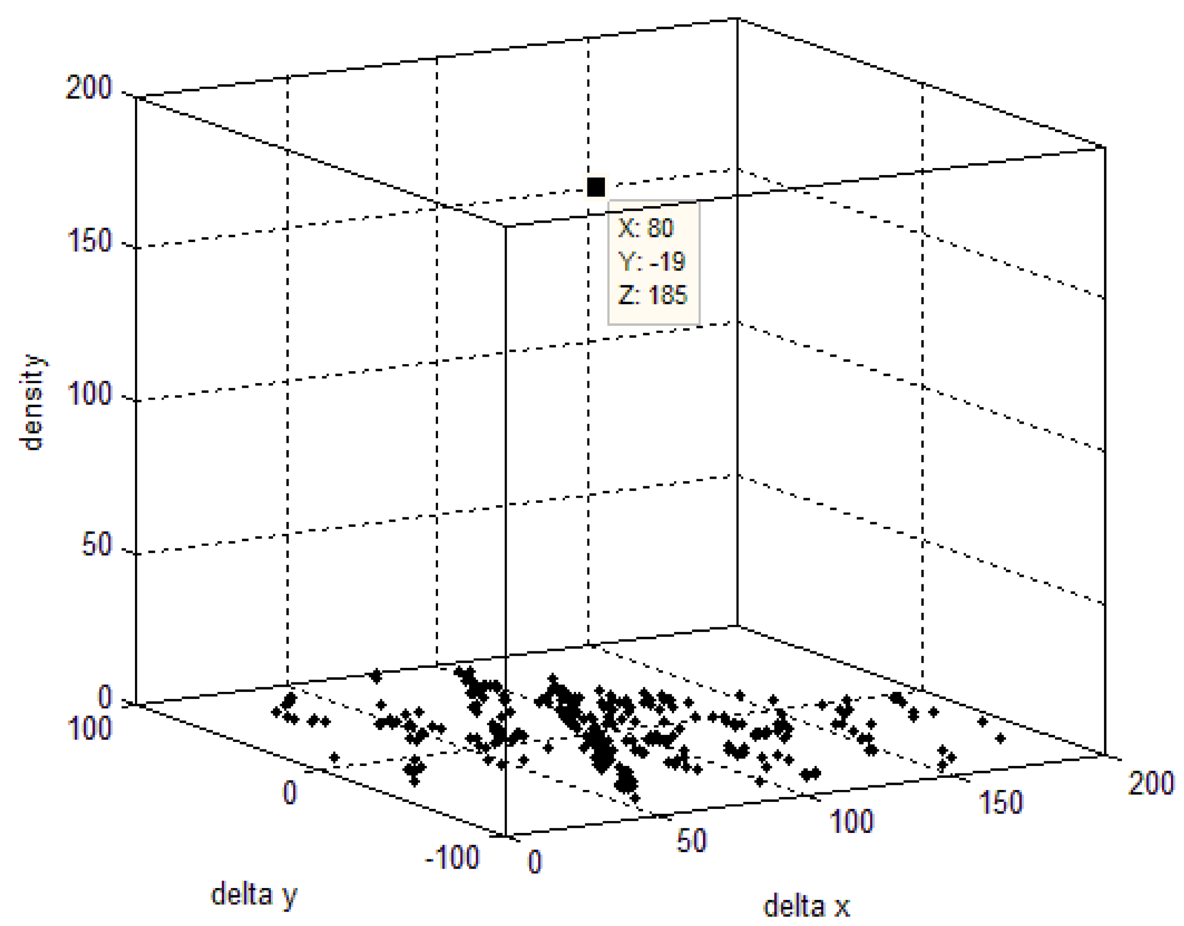


Figure 4a (Left) Projection of the point cloud density onto the vertical Δθ axis. 4b (Right) Cross section of the density map at Δθ=80 degrees.

Conclusion: The proposed ridge matching algorithm can accurately find the optimal rigid transform between two constant scale images. Since ridge features are relatively independent of normal variations in ambient lighting, it is possible to use the novel approach to track the movement of the camera with improved accuracy.

References:

[1] Galeotti et al, *Image Guided Therapy Workshop*, Oct 2011.

[2] Lindeburg, *International Journal of Computer Vision* 30(2), 79-116 (1998)

Acknowledgements:

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