A Video Processing Approach for Distance Estimation

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ABSTRACT

The paper presents a passive ranging method for estimating distances to an object using a video sequence gathered from a moving platform. The motivation is provided by potential application to object distance estimation using video data from general aviation aircraft. The method exploits scale changes of an object in the video sequence, as inferred by processing wavelet transforms of video frames, to compute distance. The underlying principles are presented along with results of bench experiments.

1. INTRODUCTION

It is desirable to enable pilots flying general aviation (GA) aircraft under visual flight rules (VFR) to estimate distances to objects such as clouds and mountains with more accuracy than that afforded by guesswork, the main approach available currently. Unlike commercial and high-end aircraft, GA aircraft are not equipped with sophisticated ranging equipment [1]. With video equipment on board, there is the potential to use changes in scale of objects in the captured video frames to estimate these distances. The basic principle is given by the heights and distances problem of trigonometry. Given the angular dimension of an object from a certain position, the change in dimensions resulting from relative movement of a known distance can be used to estimate both the extent of the object and the distance. By estimating the change in dimensions of the target images, it is possible to calculate the distance from the aircraft to the target with knowledge of distance traversed. Change of the size of target images in multiple frames has previously been proposed by Van Rheeden [2] for generic distance estimation. In [2], the size of a target is estimated from the target image associated with target information from a database integrated in the system. The algorithm measures the instantaneous horizontal and vertical dimensions of the detected target to decide the size of a target image. To compensate for the possible errors caused by incorrect size determination of the target, the method uses a pre-saved database of known targets. Therefore, if a target is unknown a priori, the approach does not guarantee its accuracy.

We propose an approach that uses wavelet transform-based multiscale decomposition. The wavelet transform generates several sub-images from an input image at multiple levels. Thus more information is available from a single image to estimate the scale change. Furthermore, the wavelet transform has the ability to detect multiscale edges of an object in an image. The distribution of the multiscale edges is a function of the size of the target, and it can be used for detection of scale changes between two target images in different frames. At this time, the algorithm has been tested on synthetic and tabletop experimental data.

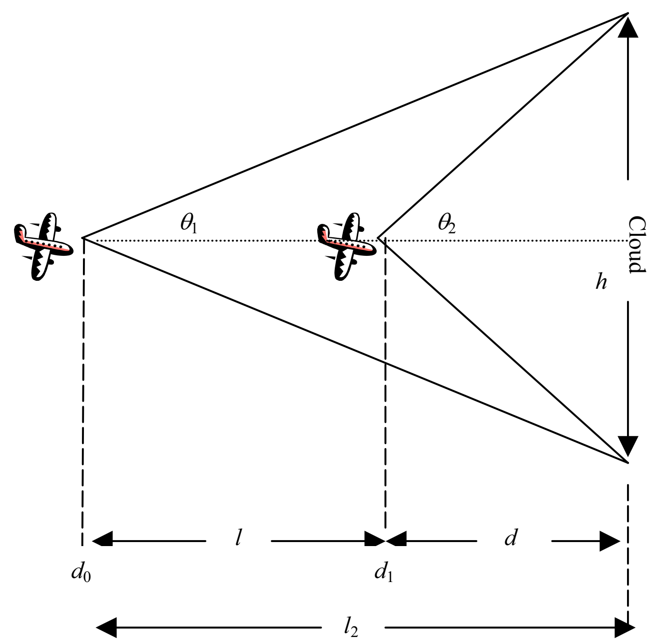

Figure 1. Computation of the distance from scale change and flight distance.

2. ALGORITHM DEVELOPMENT

The key property of the wavelet transform we use is the scaling property. Suppose $F(a,b)$ is the continuous wavelet transform (CWT) of a function $f(x)$ with respect to a wavelet $\psi(x)$,

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\psi_{a,b}(x)dx \quad (1)$$

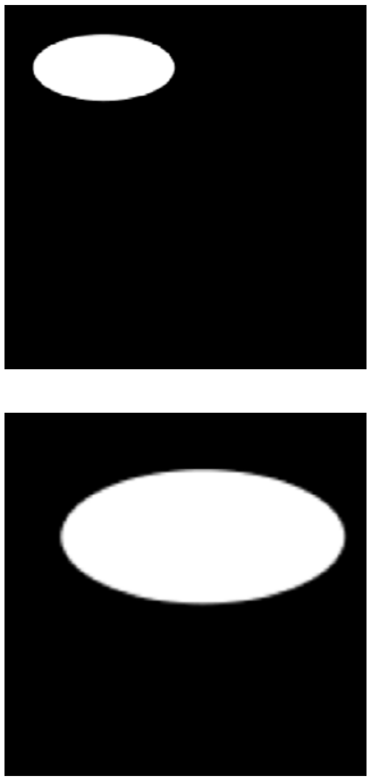

Figure 2. Test images, (Top) original, and (Bot) scaled image by $s = 2$

where $\psi_{a,b}(x) = \left[\psi\left(\frac{x-b}{a}\right)\right] / \sqrt{|a|}$. Then the CWT of $f(A(x-B))$, a scaling of $f(x)$ by A and shifting by B, is equal to [3]

$$F(Aa, A(b-B)). \quad (2)$$

Thus, the scaling in the argument of the function is captured by the scale argument of the CWT. The scaling property holds for two-dimensional CWTs as well. In working with images, we propose to estimate scale changes of a target using the undecimated wavelet transform introduced in [4] since we cannot use the CWT.

We now relate scale changes to distances. Let s be the scaling factor between target images detected in two frames taken at two locations d_0 and d_1 as illustrated in Figure 1, that is,

$$s = \frac{\text{size of target image at } d_1}{\text{size of target image at } d_0} = \frac{\tan\theta_2}{\tan\theta_1}. \quad (3)$$

Here size refers to linear dimension. Then the distance d from d_1 to the target can be computed from s and the distance, or baseline, $l = |d_0 - d_1|$ as

$$d = \frac{l}{s-1}. \quad (4)$$

Let W_n^x and W_n^y be the n^{th} level coefficients along the x and y directions respectively, of an undecimated, separable, orthogonal wavelet transform of an image I for $n = 1, 2, \ldots, N$, where N is the total number of decomposition levels. These wavelet coefficients contain the gradient information at each decomposition level. The magnitude of the gradient at a level n is computed as [4]

$$M_n = \sqrt{(W_n^x)^2 + (W_n^y)^2} \quad (5)$$

We found the variance of the gradient distribution across scales as providing a good indicator of object size. Sample probabilities are obtained from the magnitude of the gradient in (5) as

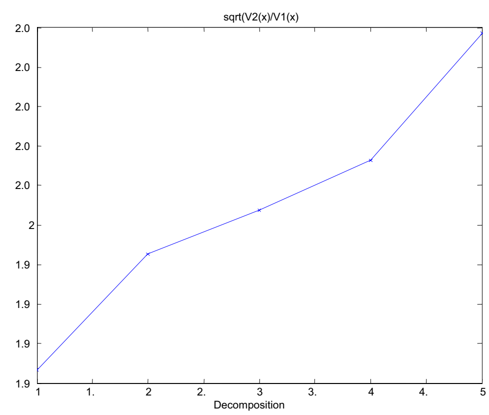

Figure 3 s_x vs n

$$P_n = \frac{M_n^2}{\sum_{xy} M_n^2}. \quad (6)$$

Using (6), the sample variances of multiscale edges along the x, y directions are computed as

$$V_{x,n} = \sum_{x,y} (W_n^x - M_{x,n})^2 P_n \quad (7)$$

$$V_{y,n} = \sum_{x,y} (W_n^y - M_{y,n})^2 P_n \quad (8)$$

where

$$M_{x,n} = \sum_{x,y} W_n^x P_n \quad (9)$$

$$M_{y,n} = \sum_{x,y} W_n^y P_n. \quad (10)$$

Because we decompose an image up to N levels, we have N such variance data along each dimension.

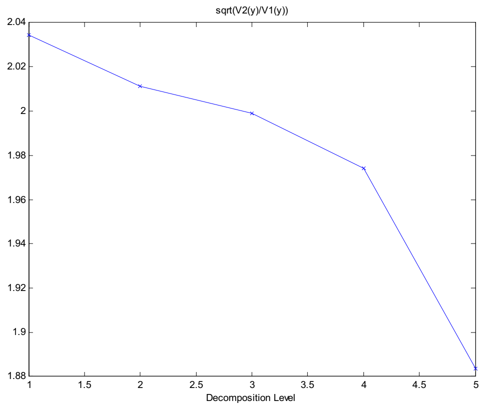

Figure 4. s_y vs. n

Average values of the variance $V_x = ave[V_{x,n}]$ and $V_y = ave[V_{y,n}]$ are used for computation of the scale factor s. Let V_{x0} and V_{x1} be the averaged variances from images I_0 and I_1 along the x direction. V_{y0} and V_{y1} are also defined similarly for the *y* direction. Then scale factor s_x and s_y for each axis between two images can be computed by

$$s_x = V_{x1}/V_{x0} \tag{11}$$

$$s_y = V_{y1}/V_{y0} \tag{12}$$

Finally, the overall scale factor estimate is obtained as

$$s = \frac{s_x + s_y}{2}. \tag{13}$$

3. RESULTS

Demonstration of scaling factor estimation

The first experiment was implemented with two images with different sizes shown in Figure 2. The second image was generated with a known scaling factor $s = 2$ from the first image. These images were decomposed into a 5-level wavelet transform using a quadratic spline wavelet [4].

The variance of multiscale edges in each image was computed using (7) through (10). Since we used $N = 5$, we have a total of 10 estimates (= the number of decomposition level multiplied by 2). Figures 3 and 4 show the estimated s values as a function of decomposition level *n* for *x* and *y* directions. The scaling factor *s* was computed using (13). We obtained a value of s = 1.9927, quite close to the true value of 2.

Distance estimation of one object

The second experiment is a tabletop experiment to test the procedure on distance estimation with a real object. Although in practice one would use a video camera with frames stamped by time and geolocation information, we used a still camera since it was more convenient and since the intent was merely to test if the algorithm yielded distance measurement. An object (cotton ball to simulate a cloud) was located at a fixed location and a camera moved along the straight line in front of the object (Figure 5). Images were taken by the camera at locations d_0 to d_3. The images are shown in Figure 6. The object was separated from the background using *k*-means clustering using *k = 2*

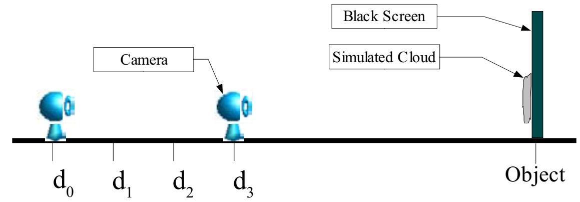

Figure 5. Experiment Setting

[5]. The object pixels were set to white and background pixels were set to zero. A 5-level wavelet transform of each image was computed. From the four locations we could choose 6 paired combinations. Scale changes were then computed for each pair using (13). Distance was computed from the scale factor and distance between the camera locations using (4). Tables 1 and 2 show the estimation results for scale and distance.

Distance estimation of two objects

The objective of the third experiment is to test the algorithm with two objects located at different points. Overall procedures are the same as the second experiment. Experimental settings are shown in Figure 7. The simulated clouds are non-occluding. Estimation results are presented in Tables 3 and 4.

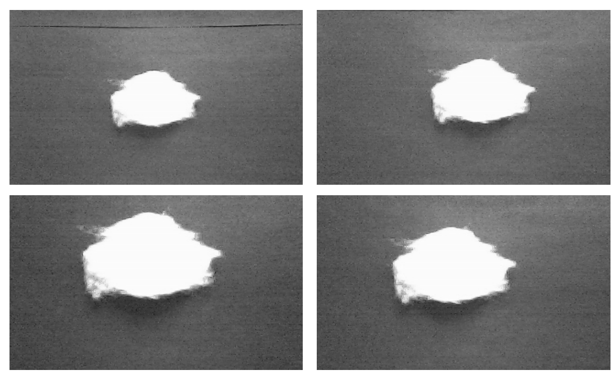

Figure 6. Clockwise from top left, pictures taken at d0, d1, d2 and d3 respectively.

4. DISCUSSION ANDCONCLUSION

The key results are: (a) development of a new wavelet transform based method for measuring scale change and distance, (b) demonstration of gradient spread across scales being a measure of object size and providing the basis for an algorithm for measuring scale change and (c) demonstration of the distance measuring algorithm with tabletop experiments. From the distance estimates provided by Tables 2 and 4, it is seen that the accuracy of the distance estimate improves with increasing baseline. The distance estimation is closely tied with segmentation. If objects are occluded then methods should be devised to focus on specific features on these objects. Work is in progress in this regard and to conduct airborne experiments.

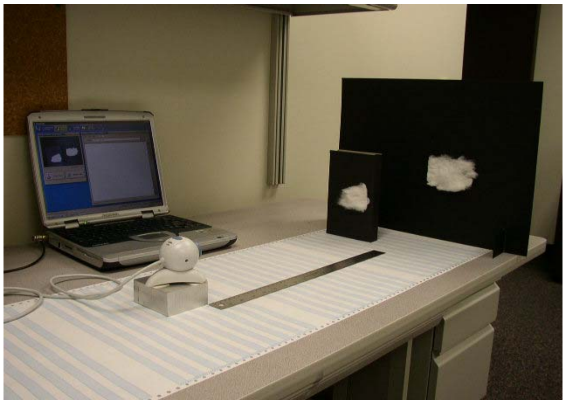

Figure 7. Experiment setting with two simulated clouds.

Table 1. Estimated scale

Distance Pairs	Estimated Scales			Distance between two points (cm)
	s	s_x	s_y	
d0 - d1	1.1431	1.1477	1.1384	4.6
d0 - d2	1.3562	1.3621	1.3504	9.7
d0 - d3	1.5328	1.5408	1.5249	13.2
d1 - d2	1.1865	1.1868	1.1862	5.1
d1 - d3	1.341	1.3425	1.3395	8.6
d2 - d3	1.1302	1.1312	1.1292	3.5

Table 2. Estimated distances

Location	Measured Distance (cm)	Distance Pairs	Distance between two points (cm)	Scales	Estimated Distance	Error (%)
d1	32.10	d0 - d1	4.60	1.1431	32.15	0.14
d2	27.00	d0 - d2	9.70	1.3562	27.23	0.86
		d1 - d2	5.10	1.1865	27.35	1.28
d3	23.50	d0 - d3	13.20	1.5328	24.77	5.42
		d1 - d3	8.60	1.3410	25.22	7.32
		d2 - d3	3.50	1.1302	26.88	14.39

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6. REFERENCES

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Table 3. Estimated scale

Distance Pairs	Object	Estimated Scales	Distance between two points (cm)
d0 - d1	1 (Left)	1.1106	5.05
	2 (Right)	1.0839	
d0 - d2	1 (Left)	1.2543	10.1
	2 (Right)	1.1832	
d1 - d2	1 (Left)	1.1294	5.05
	2 (Right)	1.0917	

Table 4. Estimated distance

Location	Distance Pairs	Object	Measured Distance (cm)	Distance between two points (cm)	Scales	Estimated Distance	Error (%)
d1	d0 - d1	1 (left)	45.60	5.05	1.1106	45.66	0.13
		2 (right)	59.40		1.0839	60.19	1.33
d2	d0 - d2	1 (left)	40.55	10.10	1.2543	39.72	2.05
		2 (right)	54.35		1.1832	55.13	1.44
	d1 - d2	1 (left)	40.55	5.05	1.1294	39.03	3.76
		2 (right)	54.35		1.0917	55.07	1.33