THE DYNAMIC MOTION ESTIMATION OF A LUNAR landER USING OPTICAL NAVIGATION

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ABSTRACT

This paper introduces a novel method for a Lunar lander’s 3-Dimensional (3-D) dynamic motion estimation during a final descending phase using optical navigation. Optical navigation is based on passive video image sequence analysis to estimate the relative motion of a lander with respect to a preselected landing site. The overall system only contains an off-the-shelf camera and a processing unit with data buses. The system under consideration therefore reduces the mass and volume of the overall system compared to the current techniques such as Radio-Link, Light Detection and Ranging (LIDAR) and Laser Ranger Finder. Together with the low operational complexity, the proposed system reduces mission cost and increases system reliability. The video image sequence analysis method is based on the Continuous Wavelet Transform (CWT), which is used to estimate the 2-Dimensional (2-D) apparent motion accurately and efficiently. The 3-D relative motion of a lander can then also be estimated accurately and efficiently. A digital video image sequence block, obtained by an onboard navigation camera, is used as an input to the propose estimation method. At each time sample, the video sequence is analyzed using CWT and the 2-D image motion is estimated. A geometry mapping for a perspective projection camera model is then used to map the 2-D image motion onto the 3-D relative motion of the lander. The output is the 3-D dynamic motions of the lander, which is sent to the Attitude Determination and Control System (ADCS) to perform the lander’s attitude control task. In this article, we provide the motion modelling of a Lunar lander during a descending phase from an initial altitude of 10 kilometers with a duration of descent of 100 seconds and the correspondence between 3-D lander’s motion and 2-D video image motion. The video image analysis method using CWT is also used to estimate the 2-D apparent motion of the incoming video sequence form a navigation camera. Numerical simulation of the estimated Lunar lander’s 3-D translation motions are shown to verify the proposed method. The analysis of the results shows that the proposed method allows for the real time estimation of the lander’s motion with better than 1% accuracy in real time. The proposed method has achieves highly accurate motion estimation with significant saving of cost, mass and volume. It also has the advantage of being easy to implement in real time.

1. INTRODUCTION

In space exploration, landers play an important role in the close exploration of celestial objects other than Earth. Landers can be found in two categories: robotic landers and manned landers. Robotic landers have the advantage of low cost, long mission lifetime compared to manned landers due to the protection of astronauts specially in the beginning exploration. Over fifty landers have been launched but eleven ended as mission failure. Among these eleven
mission failures, nine were due to the navigation, control and communication system of the lander. Future landing missions will therefore require an autonomous and reliable navigation to prevent mission failure, independently from the quality of the radio-link or other complex system. On the other hand, the recent trend points towards smaller lander’s with more compact equipments. Subsystems will therefore have to be characterised by low cost, low mass and volume, easy implementation and operation, high efficient and accuracy. All these factors have motivated the design of a new generation optical navigation system for a lander landing mission.

In January 2004, Spirit the first of two rovers of the Mars rovers of Mars Exploration Rover (MER) mission built by the National Aeronautics and Space Administration (NASA) to land successfully. Three weeks later, its twin, named Opportunity, also landed on the other side of the Mars surface successfully. Since then, both rovers have been very successful in accomplishing their mission objectives and given extensive new information for Mars exploration. This has shown the feasibility of optical navigation and the advantages of in low mass and volume, less operational complexity and the capability of estimating the horizontal velocity of Spirit and Opportunity rovers. The Descent Image Motion Estimation System (DIMES) developed by the Jet Propulsion Laboratory (JPL) took three images during the descending phase at three time instants in time (which the time at the image were taken are known from the ADCS data). A processing was performed to find the correspond areas corresponding to these three images. A correlation method was then used in parallel to determine the translation caused by the landers in the horizontal direction with respect to the landing site. Given that the estimation of the lander’s horizontal velocity was only performed at three discrete times, it was not possible to continuously track the horizontal velocity to independently operate the lander. To overcome this issue, a system based on video image sequence is required to work independently with regular and more frequent time samples.

Andrew E. Johnson and Larry H. Matthies at JPL proposed another method for the navigation of a lander, landing on a small body such as Comets or asteroids. During the descending phase, the algorithm is based on feature detection and tracking. For each two images, Shi-Tomasi-Kanade feature detection method is used to detect and track all the features in those images. A linear algorithm and non-linear algorithm are then applied to estimate the 5 Degree of Freedom (5-DOF) motion. A structure-based scale estimation is then used to estimate the depth of those features at the scene with laser altimeter data to complete 6-DOF motion estimation. This method overcomes the discontinuity between the estimations described in DIMES with high accuracy. However, another issue in here is that the feature based method is time consuming and the image sequence obtained from the onboard navigation camera must have distinctive features and a low level of noise. Thence, this method is highly dependent on the image quality and the features on the landing site. A similar method developed by Shuang Li, Hutao Cui and Pingyuan Cui in.

A new method is therefore needed to estimate the lander’s motion parameters accurately using a sequence of images, with less sensitivity to noise, without feature detection and tracking. In this paper, a method based on CWT for video image sequence analysis is proposed. During the descending phase, each image of the video image sequence obtained from the navigation camera, shows intensity differences. For example, the edge of a crater on the Moon and the shadow of that same edge have different intensities. When the lander descending towards the landing site, all these intensity differences are changing as well, and those changes follow certain trajectories, depending on the lander’s altitude motion. The CWT can be performed on the video image sequence to estimate those trajectories, and then the 3-D lander’s altitude can then be recovered from those estimated trajectories. This method is feature free and robust against noise. The complete algorithm is describeld in Section 4.
The paper is organised as follows. A lander’s motion modelling is introduced in Section 2., which introduces the coordinates employed to formulate the problem and links the lander’s 3-D descending motion to the apparent motion on 2-D video image sequence. In Section 3., some properties of the CWT are given with an example of Morlet wavelet described in. Section 4. describes the algorithm proposed in this paper. Numerical simulations of the vertical and horizontal translation motions of the lander are carried out and the simulation results are analysed in Section 5. Finally, the paper’s conclusions are given in Section 6.

2. MOTION MODELLING

During the descending phase, the preselected landing site is assumed as a flat area on the Lunar surface. The lander is assumed as a point mass and the navigation camera is modelled as a pin-hole camera with the optical center is the center mass of the lander. The lander starts at an initial attitude of 10 kilometers with a time duration of 100 seconds. Three frame systems are used to show the relative position of the lander which include a world frame which is the attitude frame , camera frame and body frame of the lander. The relative motion of the lander is divided into four categories with respect to the 2-D apparent motion on the image plane which are named as: vertical translative, horizontal translation, yaw rotation, pitch and/or roll rotation.

2.1 Coordinate System

The attitude frame is indicated using a set of capital letters of X – Y – Z in the Cartesian form. The body-frame is the coordinates of the lander itself with the origin in the centre mass of the lander and represented by \( x_b - y_b - z_b \). The camera coordinates is a 2-D coordinates represents the camera image plane and is indicated as \( x_c - y_c \). These three coordinates are illustrated as:

![Coordinate System Diagram](image)

Fig. 1. The Coordinate System: 1) X – Y – Z is the attitude frame; 2) \( x_b - y_b - z_b \) is the body frame and 3) \( x_c - y_c - z_c \) is the camera frame.

The origin of the camera frame is the lander center of mass. The camera Frame is defined such that the \( x_c - y_c \) is in parallel with lander’s body frame \( x_b - y_b \) and the optical axis is in the direction of \( z_c \). The attitude frame is defined such that the \( X - Y \) plane is the landing site plane. The Z axis is in the direction of \(- z_b\).

2.2 Camera Projection Model

As mentioned above, the camera model is a pinhole camera with a perspective projection and it is shown in Figure 2.2.
Any point on the landing site $P(X, Y, Z)$, and its projection $p(x, y)$ can be written as the following relation in the lander’s body-frame:

$$p = f \frac{P}{Z}$$

where $f$ is the focal length of the navigation camera and $p = [x, y, f]'$, $P = [X, Y, Z]'$ with $'$ is vector transpose. In here the $Z$ component can be replaced by the lander’s attitude $h$.

### 2.3 Lander’s Motion Modelling and the Correspondent 2-D Apparent Video Image Motion

The landing site is a static scene, and the lander (or the navigation camera) is moving with respect to the landing site. This scenario suggests that the motion of the lander is needed to be recovered. Therefore, an affine motion model can be used to represent the lander’s motion accurately which leads to the following four motion case.

#### 2.3.1 Lander’s Altitude Motion

The lander’s altitude motion can be modelled as a 3-D rotation and translation in the attitude frame. If we assume that a point on the landing site is represented by a vector $P_0 = [x_0, y_0, z_0]'$ in lander’s body-frame, after the lander has performed a 3-D rotation and translation, the same point on the landing site can be represented as $P_t = [x_t, x_t, x_t]'$ in the body-frame which is defined as:

$$P_t = R \cdot P_0 - T'$$

where $R$ and $T$ are the 3-D rotation matrix and translation matrix. If we chose a set sequence of rotation of “yaw-pitch-roll”, then the rotation matrix can be decomposed as following:

$$R = R_{-\text{yaw}} R_{-\text{pitch}} R_{-\text{roll}}$$

where the yaw rotation $R_{-\text{yaw}}$, the pitch rotation $R_{-\text{pitch}}$ and the roll rotation $R_{-\text{roll}}$ can be expressed as:

$$R_{-\text{yaw}} = \begin{bmatrix} \cos \alpha_{\text{yaw}} & \sin \alpha_{\text{yaw}} & 0 \\ -\sin \alpha_{\text{yaw}} & \cos \alpha_{\text{yaw}} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_{-\text{pitch}} = \begin{bmatrix} \cos \alpha_{\text{pitch}} & 0 & -\sin \alpha_{\text{pitch}} \\ 0 & 1 & 0 \\ \sin \alpha_{\text{pitch}} & 0 & \cos \alpha_{\text{pitch}} \end{bmatrix}$$

$$R_{-\text{roll}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha_{\text{roll}} & \sin \alpha_{\text{roll}} \\ 0 & -\sin \alpha_{\text{roll}} & \cos \alpha_{\text{roll}} \end{bmatrix}$$
2.3.2 Vertical Translation

Vertical translation is the lander descending in the $z_b$ direction in the attitude-frame. This lander’s motion alone results a scaling motion of the 2-D apparent motion in the video image sequence, which is illustrated in Figure 2.3.2:

![Diagram of Vertical Translation](image)

In Figure 2.3.2, $M$ and $N$ are two feature points on the landing site, through a perspective projection, their projection on the image plane at time $0$ and $t$ are $M_0$, $N_0$ and $M_t$ and $N_t$. From $M_0$ to $M_t$, there is no translation which means that $M_0$ and $M_t$ correspond to the same point on the image plane, this is true due to the $M_0$ and $M_t$ are the image of $M$ through the optical center of the navigation camera. From point $N$, its image at time $0$ is $N_0$, and the distance from $N_0$ to the optical center is $M_0N_0$ which equal to:

$$M_0N_0 = f\tan(\theta_0)$$  \hspace{1cm} (5)

and the image of $N$ at time $t$ is $N_t$ which is:

$$M_tN_t = f\tan(\theta_t)$$  \hspace{1cm} (6)

Therefore, the relationship between the $M_0N_0$ and $M_tN_t$ is:

$$M_tN_t = M_0N_0 \frac{\tan(\theta_t)}{\tan(\theta_0)}$$  \hspace{1cm} (7)

with

$$\frac{\tan(\theta_t)}{\tan(\theta_0)} = \frac{h_0}{h_t} = S_t$$

where $h_0$ and $h_t$ are the altitude of the lander at time $0$ and $t$, $S_t$ is the scaling factor of the image sequence with respect to the first frame. $S_t$ can be different if the reference frame (or the reference frame altitude) is different. Thus the vertical translation causes a scaling motion in the video image sequence. The recover of this motion means the estimation of the attitude of the lander. The intensity function of a video image sequence under this motion model is:

$$I(\vec{x}_t) = I(S_t\vec{x}_0)$$  \hspace{1cm} (8)

where $I$ is the intensity function for each frame in the video image sequence, $\vec{x}_t$ is the present image pixel position at time $t$ and $\vec{x}_0$ is the first (or reference) frame pixel position at time $0$. 

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2.3.3 Horizontal Translation

The horizontal translation of the lander cause a translation motion on the image plane both in \(x_b\) and/or \(y_b\) direction, the geometric diagram is illustrated in Figure 10. The ground point \(M\), \(O\) and \(N\) are projected onto the image plane at time \(t = 0\) and altitude \(h_0\) as \(M_0\), \(O_0\) and \(N_0\). At time \(t\) and altitude \(h_t\), the projection have changed to \(M_t\), \(O_t\) and \(N_t\). From the geometrical analysis, the following equations can be obtained:

\[
M_0 N_0 = f \tan(\theta_0) \\
M_t N_t = f \tan(\gamma_t) + f \tan(\theta_t) \\
MN = h_0 \tan(\theta_0) = h_0 \tan(\gamma_t) + h_0 \tan(\theta_t)
\]

From these equations, it is easy to observe that \(M_0 N_0 = M_t N_t\), but the position of the projection of \(M\) and \(N\) have been translated by the amount of \(M_t O_t = f v_h t / h_0 = \vec{\tau}_t\) from time 0 to \(t\) with \(v_h\) is the horizontal translation velocity in \(x_b\) or \(y_b\) direction. Same as previous section, the intensity function of a video image sequence under this motion model is:

\[
I(\vec{x}_t) = I(\vec{x}_0 - \vec{\tau}_t)
\]

2.3.4 Yaw Rotation

Yaw rotation is defined as the lander rotates itself around \(z - b\) axis. This results the lander is spinning in a plane which is parallel with the landing site. It can be illustrated in Figure 2.3.4. In this case, the lander’s motion is obvious that any projection of the landing site is rotating

![Diagram of Yaw Rotation](image-url)
with the lander at the same rate, therefore, the image motion in here is only a pure rotation in
the image plane. The intensity function of a video image sequence under this motion model
can be defined as:

\[ I(\vec{x}_t) = r_{\gamma_{yaw}\,-\,t} I(\vec{x}_0) \]  

where \( r_{\gamma_{yaw}} \) is 2-D rotation matrix which is defined as:

\[
\begin{bmatrix}
\cos(\gamma_{yaw\,-\,t}) & -\sin(\gamma_{yaw\,-\,t}) \\
\sin(\gamma_{yaw\,-\,t}) & \cos(\gamma_{yaw\,-\,t})
\end{bmatrix}
\]  

(12)

2.3.5 Pitch and Roll Rotation

Pitch (Roll) rotation is the lander rotates around \( y_b \) \((x_b)\) axis. This lander’s motion leads to a
shearing motion which is quite different compare with yaw rotation. In Figure 2.3.5 at time 0

and \( t \), the projection of the same point \( M, O \) and \( N \) result different position on the image plane
\((M_0 \leftrightarrow M_t, O_0 \leftrightarrow O_t \) and \( N_0 \leftrightarrow N_t \). The difference between these two sets of projection is:

\[
M_0 \xrightarrow{Translation} M_t = ftan(\beta_M - \gamma_{pitch\,-\,t})
\]  

(13a)

\[
O_0 \xrightarrow{Translation} O_t = f\tan(0 - \gamma_{pitch\,-\,t})
\]  

(13b)

\[
N_0 \xrightarrow{Translation} N_t = f\tan(\beta_N - \gamma_{pitch\,-\,t})
\]  

(13c)

where \( \beta_M < 0 \) is the angle between \( M_0 \) and optical center of the image plane, \( \beta_N > 0 \) is the
angle between \( N_0 \) and the optical center and \( \gamma_{pitch\,-\,t} > 0 \) is the rotation angle of the lander
around \( y_b \) axis. Using the trigonometric identities, \( f\tan(\beta_M - \gamma_{pitch\,-\,t}) \) can be written as:

\[
f\tan(\beta_M - \gamma_{pitch\,-\,t}) = f\frac{\tan(\beta_M) - \tan(\gamma_{pitch\,-\,t})}{1 + \tan(\beta_M)\tan(\gamma_{pitch\,-\,t})} = f\frac{\tan(\beta_M) - \tan(\gamma_{pitch\,-\,t})}{f + \tan(\beta_M)\tan(\gamma_{pitch\,-\,t})}
\]  

(14)

and \( f\tan(\beta_M) \) is the pixel position of \( M_0 \), therefore, Equation (14) can be rewritten as:

\[
I(\vec{x}_t) = I\left(\frac{h_0}{h_t} D\vec{x}_0\right)
\]  

(15)
whit $D$ is the deformation of the image and it is defined as:

$$D = \begin{pmatrix} \cos (\gamma_{\text{pitch}}-t) & f \sin (\gamma_{\text{pitch}}-t) \\ 0 & 1 \end{pmatrix}$$

(16)

3. CONTINUOUS WAVELET TRANSFORM

Continuous wavelet transform is a method to decompose and represent a signal by a family of scaled and translated version of a base function called mother wavelet. It was invented in the 1980s for geoscience application by Jean Morlet and Alex Grossman, but now it has been widely use in many field of application. For example, image compression, auto signal processing, dynamic modelling and video image motion estimation. In general, it can put in two categories: Discrete Wavelet Transform (DWT) and CWT. DWT is mostly applied to data compression. CWT is mainly used form data analysis due to its redundancy character.

3.1 Definition of CWT

The definition of CWT used in here is from Jean-Pierre Antoine’s book, in which is stated as:

Given an image $I \in L^2(\mathbb{R}^2, d^2(x))$, its continuous wavelet transform with respect to a fixed wavelet $\psi$, is the dot product of $I$ with the transformed wavelet $\psi_{b,a,\gamma}$, considered as function of $(\vec{b}, a, \gamma)$:

$$\Psi(\vec{b}, a, \gamma) = \langle \psi_{b,a,\gamma} | I \rangle = a^{-1} \int_{\mathbb{R}^2} \psi^* \left( a^{-1} R_{-\gamma} \left( \vec{x} - \vec{b} \right) \right) I(\vec{x}) d^2 \vec{x}$$

$$= a \int_{\mathbb{R}^2} \psi^* \left( a R_{-\gamma} \left( \vec{k} \right) \right) \hat{I}(\vec{k}) d^2 \vec{k}$$

(17)

where $a$ is the scaling factor that scales the basis wavelet (or mother wavelet) without change its shape, $\vec{b}$ is the translation factor that moves the basis wavelet or scaled wavelet across the whole image for a complete convolution and $R_{-\gamma}$ indicates the rotation motion of the image that rotates the scaled and translated wavelet in the 2-D image plane, in which is defined as:

$$R_{-\gamma} = \begin{bmatrix} \cos \gamma & \sin \gamma \\ -\sin \gamma & \cos \gamma \end{bmatrix}$$

(18)

3.2 Properties of CWT

The CWT is characterized by the following prosperities:

1. Covariant Under Translation

$$I(\vec{x}) \rightarrow I(\vec{x} - \vec{T}) \iff \Psi(a, \vec{b}, \gamma) \rightarrow \Psi(a, \vec{b} - \vec{T}, \gamma)$$

(19)

2. Covariant Under Scaling

$$I(\vec{x}) \rightarrow I(S\vec{x}) \iff \Psi(a, \vec{b}, \gamma) \rightarrow \frac{1}{\sqrt(S)} \Psi(Sa, S\vec{b}, \gamma)$$

(20)
3. Covariant Under Rotation

\[ I(\vec{x}) \rightarrow I(R_{\gamma_0}\vec{x}) \iff \Psi(a, \vec{b}, \gamma) \rightarrow \Psi(a, R_{-\gamma_0}\vec{b}, \gamma - \gamma_0) \] (21)

Therefore, for any image sequence warped with translation, scaling, rotation and deformation can be unwarped using continuous wavelet transform.

3.3 Example of CWT

In this paper a mother wavelet named Morlet is used which is after the developer Jean Morlet.\(^6,8–12\) It is defined as:

\[
\psi_M(\vec{x}) = \exp \left( -\frac{1}{2} \| \vec{x} \|^2 \right) \exp \left( -j \vec{k}_c \vec{x} \right) + \text{corr.} \tag{22}
\]

where \( \vec{k}_c \) is the center frequency with \( \vec{k}_c = [kx_c \ ky_c] \) with \( ' \) is the vector transpose. When \( \vec{k}_c \) is large enough, then corr. can be ignored. In Fourier domain, this Morlet mother wavelet can be written as:

\[
\hat{\psi}_M(\vec{k}) = \exp \left( -\frac{1}{2} \left( \vec{k} - \vec{k}_c \right)^2 \right) \tag{23}
\]

with \( \vec{k}_c = [0 \ 2\pi]' \). The wavelet family in Fourier domain with parameter \( a, \vec{b} \) and \( \gamma \) is:

\[
\hat{\psi}_{a,\vec{b},\gamma}(\vec{k}) = a \exp \left( -\frac{1}{2} \left( aR_{-\gamma}\vec{k} - \vec{k}_c \right)^2 \right) \exp \left( -j\vec{b}\vec{k} \right) \tag{24}
\]

In Figure 7, it illustrated that the Morlet wavelet in Fourier domain with different scaling factor \( a \).

![Fig. 7](image_url)

(a) \( a=1 \)

(b) \( a=4 \)

Fig. 7. The Morlet Wavelet in Fourier Domain with Different Scaling Parameters: a) \( a=1 \); b) \( a=4 \).

4. PROPOSED ALGORITHM

The Proposed algorithm is based on CWT for video image sequence analysis. The processing has the following steps:
1. Fourier Transform
   As explained before, the convolution is a multiplication in the Fourier domain. Therefore, the input video image sequence is transformed into Fourier domain first to perform the multiplication.

2. Wavelet Transform
   Wavelet transform is performed in the Fourier domain. The energy of the wavelet transform result is obtained.

3. Local Maximum Search
   Which finds the local maximum in the first video frame (or a reference video frame). Following the first energy map, the corresponding local maximum energy in the following wavelet transform energy of the following video frames are obtained. This allows to build a motion trajectory according to the intensity difference from the reference video frame with respect to the 2-D apparent motion buried under the video image sequence.

4. Geometric Mapping
   Using the geometric projection of the camera and the relation between the lander 3-D relative motion and the 2-D apparent motion, the trajectory is mapped onto the 3-D motion of the lander.

![Diagram](image)

Fig. 8. The Block Diagram of Proposed Algorithm

5. SIMULATION RESULTS

5.1 Experiment Setup

The simulation is based on the lander’s 3-D translation motion model. The video image sequence has a scaling and translation motion according the lander’s translation. The experiment is set up as follow:

1. Chose an Image
2. Chose the Motion Model
3. Construct a Video Image Sequence Based on the First Image and Motion Model
4. Perform the Proposed Algorithm
5. Compare the Results from the Algorithm with the Input Motion Model Parameters
5.2 Experiment 1

The input testing video image sequence is a block of $128 \times 128 \times 10$ with image size $128 \times 128$ and frame number is 10. There are five Gaussian function to represent five intensity different parts inside the video image sequence. The testing video image sequence is noise free. The motion model is a vertical and horizontal translation motion. Frame 1 and Frame 10 of this video sequence are illustrated as below:

![Frame 1 and Frame 10](image)

Fig. 9. Testing Video Image Sequence with Vertical Translation and Horizontal Translation Motion: a) Frame 1; b) Frame 10.

The CWT energy for those two frames with a fixed scaling factor is shown in Figure 10. From this figure, the fives peaks in both energy plot correspond to the fives intensity points in frame 1 and frame 10. When the image is scaled and translated, its CWT energy is scaled and translated.

![CWT Energy for Frame 1 and Frame 10](image)

Fig. 10. The CWT Energy Plot for Frame 1 and Frame 10 at Scaling Factor $a = 4.75$: a) CWT Energy for Frame 1; b) CWT Energy for Frame 10.

The estimation results for the trajectory of the Gaussian is shown in Figure 11 (for the Top-Right-Hand-Corner). The percentage estimation error is less than 1% as expected.

![Estimation Results](image)
5.3 Experiment 2

In here the experiment setup is same as Experiment 1 but with a 20 dB Gaussian white noise added into the video image sequence. The first and tenth frames are shown in Figure 12.

![Frame 1](image1.png) ![Frame 10](image2.png)

(a) Frame 1  (b) Frame 10

Fig. 12. Testing Video Image Sequence with Vertical Translation and Horizontal Translation Motion with 20 dB Gaussian Noise.

The CWT energy for frame 1 and frame 10 are shown in Figure 13. It clearly shows that the CWT is able to extract the intensity difference under a heavy noise presets.

Finally the trajectory estimation is shown in Figure 14. Compare with experiment 1, the results have large error which is due to the additional noise. However, this algorithm is able to extract the motion trajectory from this video image sequence with a reasonable accuracy.

6. CONCLUSION

To conclude this paper, we have introduced a novel method form a Lunar lander’s 3-D dynamic motion estimation. The numerical analysis show that this method is able to estimate the lander’s translation motion accurately using a sequence of video images. Since this method only use an off-the-shelf navigation camera, thus it can highly reduce the cost, optional complex and volume. The algorithm is applicable to any lander landing missions without modification. This algorithm can be further explored for spacecraft rendezvous missions with additional 3-D dynamic motions of target spacecraft.
Fig. 13. The CWT Energy Plot for Frame 1 and Frame 10 at Scaling Factor $a = 6.17$.

Fig. 14. The Estimated Position From Peak 5 (Top-Right-Hand-Corner).

REFERENCES


