DETECTION AND IMAGING OF MICRO-PERIODIC MOTION WITH FMCW SENSING SYSTEMS

Vincent R. Radzicki
Faculty Advisor: Hua Lee
Department of Electrical and Computer Engineering
University of California, Santa Barbara

ABSTRACT

Motion estimation is a problem that is encountered in a diverse range of technical fields. This paper demonstrates the development of a solution to the motion estimation problem in the context of imaging systems. First the general case of motion estimation is outlined followed by the special case of micro-periodic motion. The design of an FMCW microwave imaging system optimized for micro-periodic motion is then presented along with experiments and results that support the theory.

INTRODUCTION

One of the most interesting and challenging topics associated with sensing and imaging systems is the capability and accuracy of the estimation of motion and displacement. This subject becomes very important for the acoustical and microwave operating modalities in practical applications.

Two approaches for motion estimation are described in this paper. One is the parameter-based model, where the motion parameters between two adjacent image frames are formulated in the form of an orthonormal rotation matrix and a translation vector. The second approach is designed for real time detection, tracking, and direct visualization. This second approach involves the design and development of signal processing techniques for the detection and imaging of micro-oscillatory movements, which is the sensing and tracking of breathing during the search-and-rescue operations.

In this paper, the presentation includes mathematical formulation, system development, and field experiments of a microwave imaging system to demonstrate the high-precision estimation capability for micro-oscillatory movement.

BACKGROUND

Coherent imaging systems operating in either the microwave or acoustic modality are a widely used technology with applications ranging from the military, civil engineering, and geology along with many others. Certain applications require the system to image and track a target of interest that can be mobile or stationary. In the mobile case, a motion estimation procedure is required that tracks the imaged target over time.

If motion tracking is a required function, the imaging system will form a sequence of time-indexed images of the target and its environment, and the motion of the target will produce changes in the image data over time. Formation of a single image requires data collection about the scene usually through the emission and recording of a probing signal. This involves sampling reflected signals in both space and time with some form of an aperture. The sampled wavefield data is used to estimate a range profile of the scene which provides information on the relative location and return strength of the target. Lastly, the range profile information is then processed to produce the image. The formed images will be processed further to estimate the target's motion.

By modeling the target as a rigid body a parameter based approach can be utilized. If the imaging system has sufficient resolving capability this approach is applicable. In some cases, however, the resolution is fundamentally limited by the system's transmit bandwidth and the displacement of a target may be small enough to be within the resolving limits. If these small movements, or micro-movements, are oscillatory then they may produce a unique data signature that can be leveraged in the image formation process to detect and identify targets moving in this manner.

PARAMETER BASED MOTION ESTIMATION

The general method for tracking a rigid body in space involves modeling its motion as a sequence of translational and rotational shifts. This framework can be adapted to tracking a set of points that comprise the target of interest in the image. This designated set of points consists of either two or three dimensional points. Considering the case of a mobile target, the sequence of images produced each include their own set of points belonging to the moving target. The set of points can be time indexed according to the data acquisition time of their respective images.

The time indexed sets can be represented using matrix notation, and subsequently the translation and rotational shifts can be modeled with matrix operations. Let $\{q_i\}$ and $\{q_i'\}$ be the set of points extracted from two images sequentially formed one after another. A correspondence algorithm is required to match the corresponding points between these two images. Past work on this topic has explored this problem in great depth, and the presentation of this material can be lengthy on its own. Therefore, it will be assumed that the two sets have already been matched accordingly.

It has been shown that the shift matrices modeling the target motion can be solved using a sequence of linear algebra operations and is repeated here for completeness. The rotational and translational shift matrices are represented as $\boldsymbol{R}$ and $\boldsymbol{T}$ respectively. Every ith point in the set, can be expressed as

$$q_i' = \boldsymbol{R}\, q_i + \boldsymbol{T} + n_i \tag{1}$$

where n_i represents any measurement errors present. The motion estimate of the target can now be found by solving for the matrices ***R*** and ***T*** at each time instance.

The first step in solving Equation (1) is centering the two sets of points q_i' and q_i around the origin. The new set of points $\{p_i\}$ can be found to be $\{p_i'\}$

$$p_i = q_i - \left(\frac{1}{N} \sum_{i=1}^{N} q_i \right) \tag{2}$$

$$p_i' = q_i' - \left(\frac{1}{N} \sum_{i=1}^{N} q_i' \right) \tag{3}$$

These two sets can be rewritten in matrix form as

$$\boldsymbol{P} = [\, p_1, p_2, \ldots p_N \,] \tag{4}$$

$$\boldsymbol{P}' = [\, p_1', p_2', \ldots p_N' \,] \tag{5}$$

The matrices ***P*** and ***P'*** are related to each other through the rotational transform

$$\boldsymbol{P}' = \boldsymbol{R}\,\boldsymbol{P} + \boldsymbol{n} \tag{6}$$

where the noise vectos n_i have also been rewritten in matrix form as

$$\boldsymbol{n} = [\, n_1, n_2, \ldots n_N \,] \tag{7}$$

The rotation matrix ***R*** expressed in Equation (6) is now expressed in familiar form that has a well-known solution by the Method of Least Squares. By taking the singular value decomposition of the product of $\boldsymbol{P}'\,\boldsymbol{P}^T$

$$\boldsymbol{P}'\,\boldsymbol{P}^T = \boldsymbol{A}\,\boldsymbol{\Lambda}\,\boldsymbol{B} \tag{8}$$

The matrices ***P*** and ***P'*** are both known quantities which can be used to determine the implicit relationship in Equation (8). The least squares solution would be in the form of

$$\boldsymbol{R} = \boldsymbol{A}\,\boldsymbol{B}^T \tag{9}$$

The shift vector can now easily be expressed as

$$T = \frac{1}{N}\left(\sum_{i=1}^{N} q_i' - \boldsymbol{R} \sum_{\boldsymbol{i}}^{\boldsymbol{N}} q_i\right) \quad (10)$$

Equations (9) and (10) provide the motion parameters of the target between two sequential images. By continuously updating the two parameters over the entire data collection period an overall trajectory of the target can be produced. This type of tracking can provide useful information to the end user of the system, or possibly be re-used for other procedures such as target recognition or adaptively steered radar systems.

ESTIMATION OF MICRO-OSCILLATORY MOVEMENT

The previously described algorithm depends on changes in the locations of key points across the time-indexed sequence of images. For targets whose movements are within a resolution unit of the imaging system, this method will not be successful in motion tracking or even motion detection.

A typical person that is stationary normally will not move any distance greater than the resolution unit of most microwave imaging systems. Detection and tracking of breathing has been an area of interest recently in both the academic and industry communities. People have relatively low radar-cross sections compared to classical radar targets, and that makes them difficult to detect using conventional a microwave imaging system. The periodic nature of breathing can produce a distinct signature in reflected electromagnetic signals, however, that can be utilized to identify breathing targets. By analyzing the changes in microwave images over time, this periodic signature can be identified and used in image formation.

A variety of change detection algorithms for sequences of images in video data have been developed in prior work. The simplest change detection method is to apply a first order difference Equation to successive image frames.

$$\hat{p}_n(x, y, z) = s_n(x, y, z) - s_{n-1}(x, y, z) \quad (11)$$

where $s_n(x, y, z)$ is the image frame at time n and $s_{n-1}(x, y, z)$ is the image one frame earlier at time $n-1$. Any peaks in the new image $\hat{p}_n(x, y, z)$ would indicate a change between the two frames. A higher order difference equation on the image frames can also be expressed as

$$\hat{p}_n(x, y, z) = s_n(x, y, z) - 2\, s_{n-1}(x, y, z) + s_{n-2}(x, y, z) \quad (12)$$

Although these types of systems can be directly applied to microwave images, the image formation process introduces several errors onto the data from phase incoherencies, position misalignments, and other degenerative sources. Because the image formation procedure is linear, a linear change detection system and image formation procedure is interchangeable. The difference Equations (11) and (12) can directly be applied directly to collect wavefield data to yield the relationship

$$\hat{g}_n(x, y, z) = g_n(x, y, z) - g_{n-1}(x, y, z) \quad (13)$$

$$\hat{g}_n(x, y, z) = g_n(x, y, z) - 2\, g_{n-1}(x, y, z) + g_{n-2}(x, y, z) \quad (14)$$

again where $g_k(x, y, z)$ is the collected wavefield data sampled at a point in space (x,y,z) and at time n.

The estimated range profile from the collected data can also undergo the same change detection procedure which would result in a new range profile

$$\hat{q}_n(r) = \frac{1}{2}(p_n(r) - p_{n-1}(r)) \quad (15)$$

where $p_n(r)$ is the range profile at some range distance r collected at time n.

This idea of applying a change detection procedure to multiple range profiles over the collection time n was expanded to model periodic motion of a target. Defining the change in range distance of a target at time n as

$$\Delta r_n = \Delta r \sin(n\Omega_0) \quad (16)$$

and defining Ω_0 as the frequency of oscillation of the target.

The range profile at time $n+1$ recorded from a target moving in this manner would be equal to a range shifted version of its previously collected range profile

$$p_{n+1}(r) = p_n(r - \Delta r_n) \quad (17) \quad (17)$$

In the Fourier Domain this relationship can be expressed as:

$$P_{n+1}(f) = P_n(f) \exp(-j2\pi f \Delta r_n) \quad (18)$$

Assuming the only changing component in the range profile is the oscillating target, we can rewrite Equation (18) as

$$\begin{aligned} P_n(f) &= P(f) \exp(-j2\pi f \Delta r_n) \quad (19) \\ &= P(f) \exp(-j2\pi f \Delta r \sin(n\Omega_0)) \\ &\approx P(f)\, [\, 1 - j2\pi f\, \Delta r \sin(n\Omega_0)] \end{aligned}$$

where the first order expansion has been used to approximate $\exp(-j2\pi f \Delta r_n) \approx 1 - j2\pi f \Delta r_n$ given that the overall displacement Δr_n is small.

Equation (19) can then also be rewritten as

$$P(f, n) = P_n(f)$$
$$= P(f)\,[1 - \pi f\,\Delta r\, exp(jn\Omega_0) + \pi f\,\Delta r\, exp(-jn\Omega_0)] \quad (20)$$

Now taking the Discrete Fourier Transform (DFT) of *P(f,n)* across the collection index *n* yields for each frequency *f* the following distribution is produced

$$P(f, k) = P(f)\,\delta(k) - \pi f\Delta r\, P(f)\,\delta(k - N\Omega_0/2\pi) + \pi f\Delta r\, P(f)\,\delta(k + N\Omega_0/2\pi) \quad (21)$$

where *k* is the DFT index with respect to the collection time *n*.

The final frequency of oscillation of the target produces a peak in this distribution and occurs at the *DFT* index

$$k = \pm N\Omega_0/2\pi \quad (22)$$

The frequency of oscillation can be converted to *Hz* by scaling it according to the frequency of data collection F_s .

$$f_0 = \Omega_0 \cdot F_s \quad (23)$$

This information identifies which range spectrum *P(f)* in the distribution of Equation (23) is resultant from targets exhibiting periodic motion. By partitioning *P(f,k)* according to the identified oscillation index of interest, a new range profile can be computed and standard imaging techniques can be applied to form a image of ideally only the identified oscillating targets.

EXPERIMENTS AND RESULTS

To determine the accuracy of the method proposed in the previous section, specially designed experiments were conducted with people and various other targets present. A stand-off radar imaging system was utilized as the data acquisition system to collect complex wavefield data as similar to the unit shown in Figure 1. The final hardware system included a smaller antenna array for portability. The hardware comprised of an 8-port AKELA vector signal generator and measurement unit (AVSMU) , 8 ultra-wide band Vivaldi antennas, and a PC programming interface to control the radar and collect data. All signal processing and image formation was computed in the MATLAB programming environment, which produced the graphical figures presented here as well.

The experiments were conducted outside a test facility in a vacant parking lot to limit the clutter exposed to the radar. The radar was pointed at a scene that consisted of a human target standing, a stationary corner reflector, and the back wall of the parking lot as the only visible targets. Given its high RCS and stable imaging properties, the corner reflector was used as a reference point to compare the person against. The person stood in a non-moving position and breathed at a normal rate. A total of around two minutes of data was collected at different perspectives and target angles.

Figure 1: Original Hardware System

The 8 antennas were placed in a linear array with *0.17 m* spacing which produced a total array length of *1.19 m.* The multi-static transceiver collected data on each bi-static pair of antennas which produced *56* total tracks of data to form a single data frame to be used in image formation.

The radar system transmitted a stepped-FMCW probing signal with a frequency hop rate of *45000* frequency points per second. The stepped-FMCW signal is a sequence of coherent CW signals with frequencies

$$f = f_0 + k\,\Delta f \qquad where\ k = 0, 1, 2, \ldots N\text{-}1 \tag{24}$$

where f_k is the kth transmitted frequency in the original FMCW sequence and Δf is the frequency step between successive CW signals. The transmitted signal used emitted a frequency band starting from *1 GHz* to *4 GHz* with *1301* frequency points.

The frequency data $P(f_k)$ collected through an FMCW system has been shown to form a Fourier Transform pair with the range profile estimate of a target

$$P(f_k) = DFT\{\, p_n(r)\} \tag{25}$$

The range resolution of the system can be shown to be inversely proportional to the frequency bandwidth B and the speed of propagation v_p as

$$\delta = \frac{v_p}{2B} \tag{26}$$

The frequency data collected during the experiments was then processed according to the periodic detection and partitioned according to the method described earlier. This yielded new range profile data for each track of data collected by the radar that was utilized in image formation. A two dimensional scene of interest was reconstructed based on where the targets position would be relative to the radar's antenna locations. Coherent backward projection was used to form the final image by mapping the range profiles values to their corresponding range bin of interest in the reconstructed scene.

As expressed in Equation (26) the raw frequency data collected with the radar can be used in the oscillation estimation procedure. By taking a *DFT* along the collection index, and searching for a peak the oscillating frequency can be determined from Equation (24). Simple recording of the persons rate of breathing yielded a basic estimate of around 12-20 cycles per minute. Figure 2 shows the results of the procedure. A clear broadband peak can be viewed across the spectrum around 0.3Hz which is around the typical value expected. Note that some frequencies bands have overall suppressed magnitudes in this range. This is mainly due to the frequency dependent effects of person target scattering.

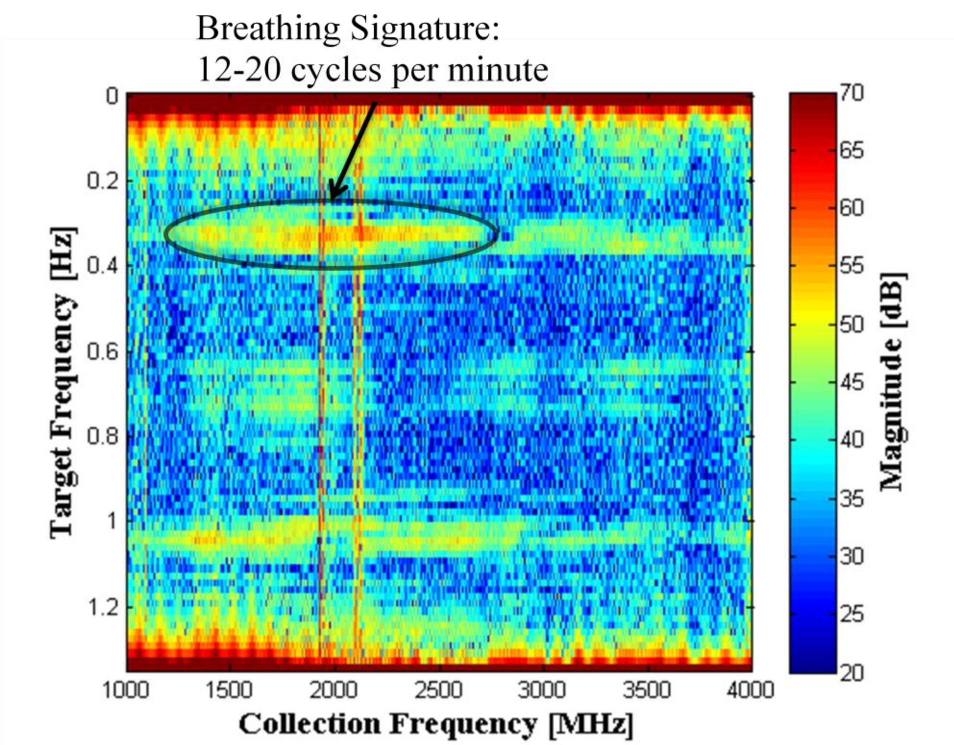

Figure 2: 2D Spectrum of Time Varying Range Profile *P(f,k)*

The results of the imaging procedure are displayed in Figure 3. Both images are displayed in the magnitude dB domain and both have been plotted with the same dynamic range of 20dB to allow for equal brightness comparisons. The first image is the result of the breathing estimation algorithm, and the second image is the unprocessed data. The processed image shows greater than 10dB gain of the breathing target compared to the unprocessed image, and also reduces the overall magnitude of all stationary targets in the scene.

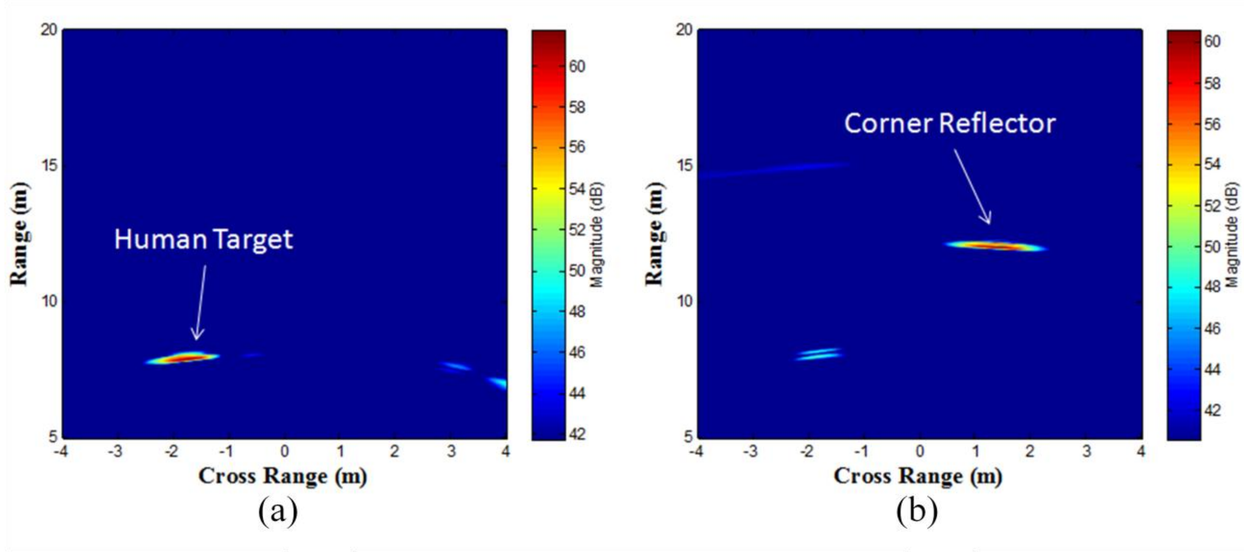

Figure 3: Back projection Imaging Results (a) Time-Varying Component and (b) Stationary Component

CONCLUSIONS

Motion estimation is a powerful tool that can be employed in imaging systems to improve performance. Many applications involve imaging moving targets, and being able to exploit this information can greatly improve the accuracy and detection capabilities of any tracking system. This type of improvement is critical when trying to image mirco-periodic movements. Breathing detection is an important problem with broad technical impact. This paper has shown that micro-periodic analysis of images is a successful way to modeling breathing for detection applications.

The design and development of a micro-periodic detection system has been presented along with experimental results demonstrating its potential for improving performance of a standard microwave imaging system. Future improvements for the system include adjustments to allow for through-the-wall imaging and tracking of walking targets.

ACKNOWLEDGMENTS

Thank you to AKELA Inc. for their generous technical support throughout the research process. Also, thank you to Professor Hua Lee for his guidance and advice with all the writing and development of the technical theory presented here.

REFERENCES

1. Hua Lee, *Acoustical Sensing and Imaging*, CRC Press, New York, January 26, 2016
2. Hua Lee and Vincent R. Radzicki, "Circular-Mode Synthetic Aperture Subsurface Imaging With MIMO FMCW Microwave Array System," in *Proceedings of the International Telemetering Conference*, Las Vegas, NV, October 2013
3. Vincent R. Radzicki and Hua Lee, " FMCW Subsurface Microwave Imaging With Hexagonal Antenna Array," in *Proceedings of the International Telemetering Conference*, San Diego, CA, October 2014
4. Arai, I., "Survivor search radar system for persons trapped under earthquake rubble," Microwave Conference, 2001. APMC 2001. 2001 Asia-Pacific , vol.2, no., pp.663,668 vol.2, 3-6 Dec. 2001
5. Hua Lee and Glen Wade, *Imaging Technology*, IEEE Press, New York, 1986.
6. Mei-Su Wu and Hua Lee, "Remote Detection and Geolocation of Breathing Subjects by High-Performance Ultra-Wideband FMCW MIMO Microwave Imaging System," *Proceedings of International Telemetering Conference*, 2011.