An Adaptive Filter Technique for Platform Motion Compensation in Unmanned Aerial Vehicle Based Remote Life Sensing Radar

Shekh M. M. Islam[#1], Lana C. Lubecke[*#2], Christian Grado[#3], Victor M. Lubecke[#4]

[#]Department of Electrical Engineering, University of Hawaii at Manoa, Honolulu, HI, USA

[*]Kalani High School, Honolulu, HI, USA

{[1]shekh, [3]cgrado, [4]lubecke}@hawaii.edu, [2]lanaip808@gmail.com

Abstract — **Unmanned Aerial Vehicles (UAVs) have demonstrated efficacy as a platform for remote life sensing in post-disaster search and rescue applications. Radar-assisted UAV respiration motion sensing technology also shows promise yet a significant technological challenge remains associated with interfering motion artefacts from the moving UAV platform. The feasibility of integrating an adaptive filter approach for the compensation of platform motion artefacts is investigated here for the extraction of respiratory motion signatures. A 24-GHz dual radar system was attached to a mechanical mover to emulating motion artefacts while measuring the motion of a robotic breathing phantom designed to reproduce breathing motion patterns. Recursive least square (RLS) and a least mean square (LMS) adaptive filter algorithms were employed to test efficacy for extracting respiratory rate from the motion corrupted breathing signal. Experimental results demonstrated that the RLS performed best with an accuracy of 98.24% for extracting the frequency of the robotic breathing phantom mover. The proposed system has several potential applications including military, humanitarian, and post-disaster search and rescue operations.**

Keywords — **Adaptive filter, recursive least square, least mean square, motion compensation.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have demonstrated potential for finding trapped or injured people in post-disaster rescue scenarios and can potentially aid with triage assessments using an on-board Radar sensor for detecting vital signs [1]. UAV-borne radar sensors can provide a broad range of information about victims which can be useful for remote assessment by rescuers [2]. Non-contact sensing of physiological motion using stationary microwave Doppler radar has shown efficacy with proof of concepts demonstrated for vital signs sensing in various applications over the past four decades, and could be a powerful triage assessment tool if implemented on a mobile platform like a UAV. However, mobile platform motion will induce extraneous noise which will add an undesired phase component to the radar baseband signal making the extraction of respiratory information much more challenging [3,4].

Prior UAV-borne vital signs radar research has focused on the use of the received signal strength indicator (RSSI) and RF Direction of Arrival (DOA) for commercial radar modules to provide flight control feedback to stabilize the air-borne platform [4-5]. While the results were promising, the extent to which the platform can be stabilized is not sufficient for challenging real-world environmental conditions and ultimately requires additional noise compensation signal processing. Suppression of clutter noise has also been considered, with the assumption of a stable radar platform [6]. While optical image-processing systems have been created to measure respiration and heart rates from a remotely operated vehicle (i.e. drone), such systems are will likely prove inadequate under common post-disaster conditions such as darkness, fog, and smoke, and cannot resolve respiratory motion when subjects are wearing loose clothing [7]. Radar measurements are unaffected by light conditions and can penetrate normal clothing. One significant limitation of using radar on a moving drone to measure vital signs is that the movement of the drone will corrupt the measurement of heart and respiratory motion. Thus, a reliable and robust motion compensation technique is required to bring this sensor technology into real world implementations.

The use of an adaptive filter for motion compensation for UAV-borne remote radar respiration sensing is investigated here, with preliminary results based on a testbed using robotic movers to simulate drone and breathing motion reported. An indoor scenario is examined, with a secondary radar used to track UAV motion with respect to a stationary clutter point (ceiling) to provide a reference which can be cancelled from the primary radar measurement of a respiration-motion target. An approach for using least mean square (LMS) and recursive least square (RLS) adaptive filter algorithms is described, with performance compared. The RLS algorithm performed best with a respiration frequency measurement accuracy of 98.24%.

II. Theory and Background

A. Theory of Doppler Radar Transceiver

A typical continuous wave (CW) Doppler radar vital signs transceiver sends a continuous electromagnetic signal towards a human subject and measures the phase change of the reflected signal associated with physiological motion [6-8]. The phase change of the reflected signal is directly proportional to the minute movement of the chest surface due to cardio-respiratory activities [3,4,6]. In a stationary CW system, stationary clutter is detected only as a dc offset. The radar transmits the waveform as:

$$T(t) = Acos(2\pi f_t t + \phi(t)) \quad (1)$$

and the received waveform is:

$$R(t) = Acos(2\pi f_t t + p(t) + \theta + \phi(t - \frac{2R}{c}) \ , \quad (2)$$

where, A is the amplitude, f_t is the transmitter frequency, $\phi(t)$ is the transmitter phase offset, θ is the fixed phase offset inherent in the receiver hardware, $p(t)$ is the phase modulation from the respiration motion and $\phi(t - 2R/c)$ is the phase delay due to roundtrip signal propagation. For CW Doppler radar, the phase change of the backscattered signal from the target is the critical measurement. Defining the physiological motion of the thorax expanding and contracting as $x(t)$, the phase modulation detected by radar is defined as: $p(t) = \frac{4\pi}{\lambda} x(t)$. After down-conversion of the receiver signal the simplified form is:

$$S_{resp}(t) = \cos(\frac{4\pi A}{\lambda} \sin(\omega_1 t)) \quad (3)$$

and the platform signal is represented as:

$$S_{plat} = \cos\,(\frac{4\pi B}{\lambda} \sin(\omega_2 t))\ , \quad (4)$$

where B is the platform motion amplitude. The combined composite motion of detected by the radar sensor in an UAV platform is:

$$S_{composite}(t) = \cos\,(\frac{4\pi A}{\lambda} \sin(\omega_1 t) + \frac{4\pi B}{\lambda} \sin(\omega_2 t)), \quad (5)$$

where, ω_1 is the angular frequencies for the respiration signal to be recovered and ω_2 is the undesired platform motion that must be supressed. For an indoor triage radar application, a primary radar module would be mounted on the bottom of the drone, facing the subject, and a secondary radar would be mounted on top of the drone, facing the ceiling. The primary radar captures the breathing movement combined with the movement of the drone, while the second radar module captures only the movement of the drone. Fig. 1 illustrates the indoor

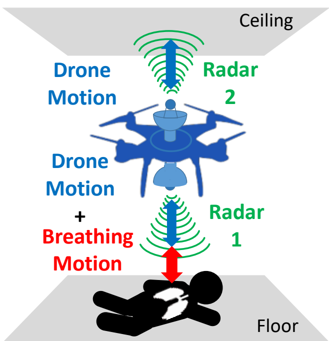

Fig. 1. Concept for an indoor search and rescue drone. One radar can be attached to the UAV (drone) bottom, facing the subject (Radar 1), while the second is attached on top facing the ceiling (Radar 2). Radar 1 measures drone motion and breathing motion while Radar 2 measures only drone motion. An adaptive filter can use Radar 2 data as a basis to filter drone motion from Radar 1 to produce a signal of only breathing motion.

drone radar concept. In effect, the clutter reflection associated with the stationary environment approximates an error correction signal to compensate for drone-motion noise. The system could potentially also operate in locations without a ceiling by pointing the secondary radar at the floor, but an angle which keeps the subject out of its view.

B. Theory of Adaptive Filter Techniques

An adaptive noise canceller (ANC) has a primary input and a reference input. The primary input receives a signal, s, that is corrupted by the presence of noise, n, which is uncorrelated with the signal [9-12]. Fig. 2 illustrates the adaptive noise cancellation technique. The reference input receives a noise n_0 uncorrelated with the signal but correlated in some way with the noise, n. The noise n_0 passes through a filter to produce an output n' that is a close estimate of the signal noise, n. The noise estimate is subtracted from the corrupted signal to produce an estimate of the signal s'. The output of the ANC system is:

$$s' = s + n - n' \quad (6)$$

$$s'^2 = s^2 + (n - n')^2 + 2s(n - n') \ . \quad (7)$$

Taking expectation on both sides and assuming s is uncorrelated with n_0 *and* n' we have

$$E[s'^2] = E[s^2] + E[(n - n')^2] + 2E[s(n - n')] \quad (8)$$

$$= E[s^2] + E[(n - n')^2]\ . \quad (9)$$

The basic adaptive filtering technique is based on adjusting the filter coefficients to minimize $E[s'^2]$ as signal power $E[s^2]$ will be unaffected [10-12].

$$\min E[s'^2] = E[s^2] + \min E[(n - n')^2] \quad (10)$$

There are two popular algorithms for minimization of $E[s'^2]$ one is least mean square (LMS) and another is recursive least square (RLS) [9-12]. An LMS filter tries to adapt its coefficients based on the differences between the desired signal and actual signal minimum differences [9-12]. On the other

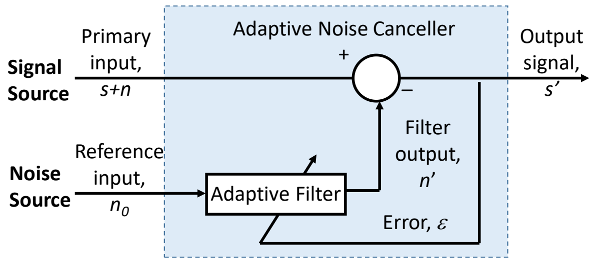

Fig. 2. Block diagram illustration of the generalized adaptive noise cancellation (ANC) method.

hand, RLS recursively finds the filter coefficients that minimizes the weighted linear least square cost function of the input signals [11-12].

III. Experimental Setup and Data Collection

Two 24-GHz KMC4 monopulse radar modules were used, each with two channels (I_1, Q_1) connected to low noise amplifiers (LNA's) (SR560). The LNA's were ac-coupled with gain of 200, and low-pass filtered with cut-off frequency of 30 Hz, and the LNA outputs were connected to a DAQ. Finally, a

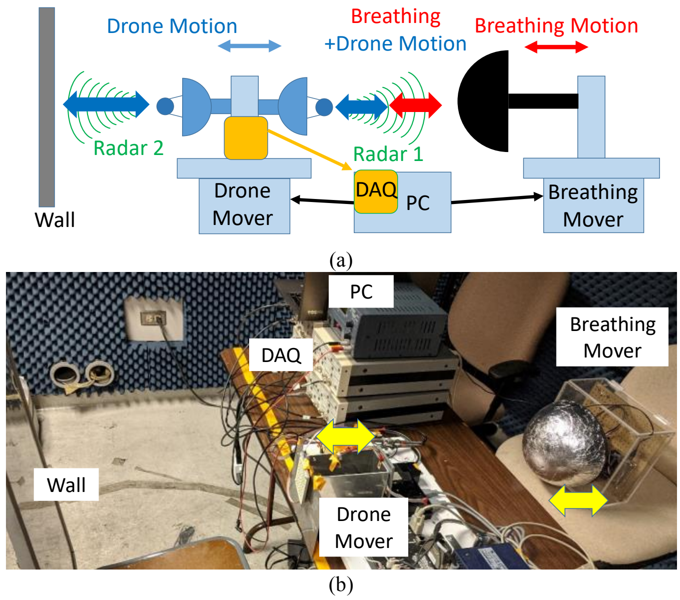

Fig. 3. Concept, (a), and experimental setup, (b), for measurements using two 24-GHz K-MC4 radar receivers. The radar transceivers were mounted on one mechanical mover, and a second respiratory phantom mover was used to emulate respiration motion.

customized MATLAB interface was used to capture the signals. The two radar modules were mounted on one mover which represented drone motion. One radar module was pointed at a second programmable robotic phantom mover, which was designed to simulate dynamic respiratory motions associated with breathing [13]. The other radar module faced a stationary wall, which represented the ceiling or another non-moving reference surface. Fig. 3 illustrates the concept and the hardware setup for the experiment.

IV. Results

In order to assess the effectiveness of the LMS and RLS filter designs, initial measurement simulations were conducted for both sinusoidal and pulse breathing motion signals at a frequency of 0.2 Hz. For dc drift compensation, the LNAs were ac-coupled and the mean part of the signal from the samples was removed in MATLAB post processing. An RLS filter with an order of 32 and an initial covariance estimate of 0.1 was implemented, along with an LMS filter with an order of 32. Fig. 4 illustrates the reconstructed signal for a pure sinusoidal simulated respiration signal input and a random number generated noise signal, achieved using the RLS filter. The effectiveness of the LMS and RLS filters were both also tested with real data experiments. An additional radar module was not available to make a simultaneous respiration-motion-only reference measurement. However, it was assumed that the respiration phantom mover had a regular, repeating movement pattern, and so an initial measurement its motion could be made with the drone motion mover turned off, and used as a reference signal to compare with the reconstructed breathing signal once the drone mover was turned on. Fig. 5 shows a plot of the experimental result for the reconstructed signal using the RLS adaptive filter. In the plot it is evident that the reconstructed signal using the RLS filter closely matches the original signal recorded during initial reference measurement. For comparative analysis between two different adaptive filter algorithms, the mean square error and cross-correlation coefficient of the signal were also investigated. Recovery of the oscillation frequency of the respiration phantom mover was targeted as it represented

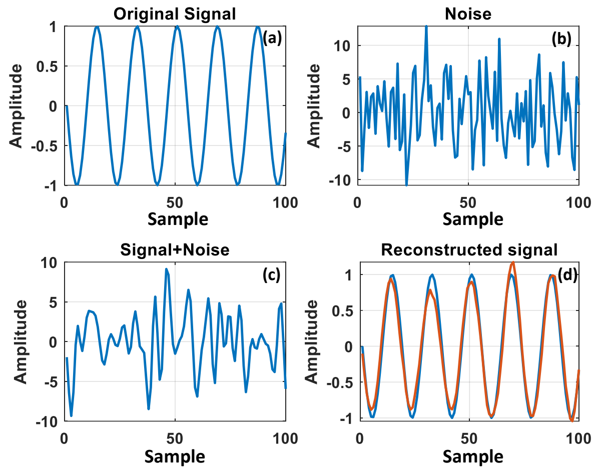

Fig. 4. Respiration motion was initially simulated with sinusoidal motion, (a), and an RLS filter was applied to reconstruct the breathing motion signal from the combined mixture of signal and noise, (d).

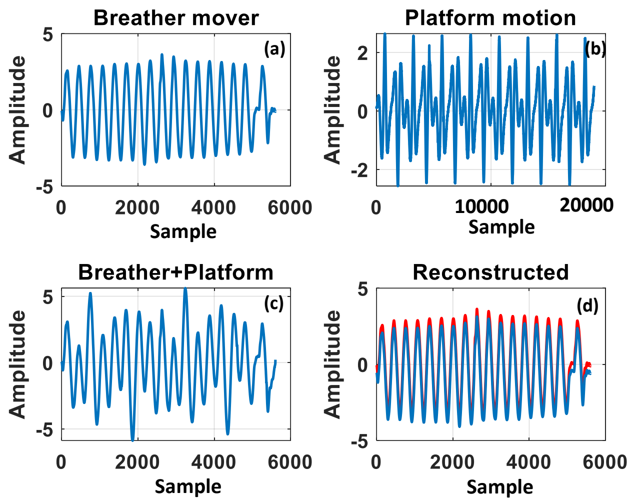

Fig. 5. Experimental results using an RLS adaptive filter with robotic movers. Breather motion episode, (a), platform motion or simulated drone movement (b), and combined breather motion and platform motion are shown, along with the reconstructed signal obtained using the adaptive filter, (d).

the breathing rate of interest which would be useful for triage decisions. A Fast Fourier transform (FFT) was used on the reconstructed signal to extract the highest vibrational frequency content using the LMS and RLS algorithms. Fig. 6 illustrates the reconstructed signal frequency domain plots. The actual respiration phantom mover frequency was around 1 Hz. The performance metric for both implemented adaptive filters was calculated based on the following equation:

$$accuracy = 100 - \left(\frac{|actual\ frequency - reconstructed\ frequency|}{actual\ frequency} * 100\right) \tag{11}$$

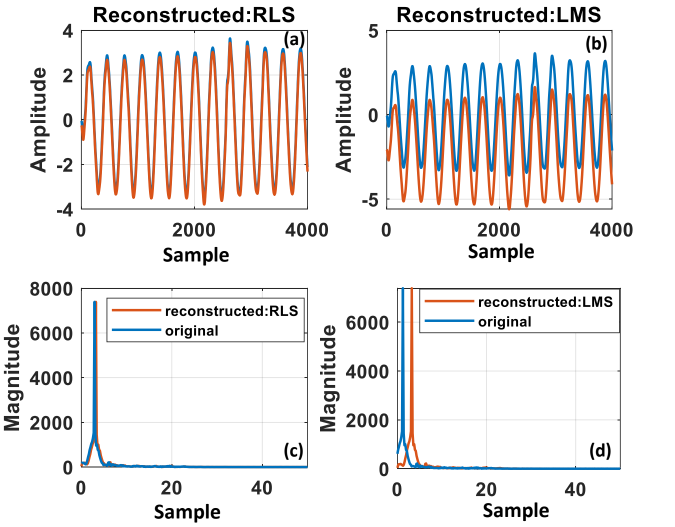

Fig. 6. Reconstructed time domain signals using an RLS filter, (a), and an LMS filter, (b). The FFT plots for the signal reconstructed using an RLS filter, (c), and an LMS filter, (d), are also shown.

After reconstructing the signal using the RLS filter, the extracted frequency was 1.02 Hz which matches the actual 1 Hz motion. For the LMS filter the extracted signal frequency was 1.12 Hz. For the comparative analysis, an FFT was performed on 6000 one-minute data samples to extract the breathing rate information. Compared to the LMS algorithm, the RLS approach offers less error which offsets the fact that it requires more computational feedback. More computational feedback provides better adaptation of filter coefficients hence provides less error [9-13].

V. Conclusion

The feasibility of using an adaptive filtering approach for motion compensation in respiration motion measurements from a moving UAV platform was evaluated. From the experimental results using robotic movers to represent UAV and respiratory motion for an indoor scenario, it was demonstrated that by incorporating the RLS algorithm in a Doppler radar physiological monitoring system, breathing rate can be extracted from motion corrupted signals when a secondary radar targeting stationary clutter is used to separately assess UAV motion. The tested RLS algorithm outperformed other algorithms due to its iterative feedback mechanism for adapting appropriate filter coefficients, resulting in an accuracy of 98.24%. The results indicate promise for use of this method in suppressing the interfering motion of a UAV platform when making radar measurements of respiratory motion for a subject situated beneath the moving aircraft.

Acknowledgement

This research was supported in part by the National Science Foundation (NSF) under grant IIS-1915738.

References

[1] V. Ferrara, "Technical survey about available technologies for detecting buried people under rubble or avalanches," *WIT Transactions on The Built Environment*, vol 150, pp. 91-101, May 2015.

[2] D. Choudhury, "5G wireless and millimeter wave technology evolution: an overview", in *IEEE MTT-S Int. Microwave Symposium (IMS)*, May 2015, pp. 1-4.

[3] C. Li, V. M. Lubecke, Olga Boric-Lubecke and J. Lin, "A review on recent advances in Doppler radar sensors for non-contact health monitoring" *IEEE Trans. Microwave Theory and Technique.*, vol. 61, no. 5. pp 2046-2060, May 2013.

[4] Robert H. Nakata et. al, "Motion compensation for an Unmanned Aerial Vehicle remote radar life Sensor," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems.*, vol. 8, no. 2, pp. 329–337, June 2018.

[5] Robert Nakata, Scott Clemens, Alex Lee and Victor M. Lubecke "RF techniques for Motion Compensation of an Unmanned Aerial Vehicle for remote radar life sensing," in *Proc. IEEE International Microwave Symposium (IMS)*, 2016.

[6] C. Li, and J. Lin, "Random body movement cancellation in Doppler radar vital sign detection" *IEEE Trans. Microwave Theory and Technique.*, vol. 56, no. 12. pp 3143-3152, Nov 2008.

[7] Ali Al-Naji, Asanka G. Perera, and Javan Chahl, "Remote Monitoring of Cardiorespiratory Signals from a Hovering Unmanned Aerial Vehicle", *Biomedical Engineering OnLine* 16.1(2017):1-20.

[8] Shekh M M Islam, Ashikur Rahman, Ehsan Yavari, Meheran Baboli, Olga Boric-Lubekce and Victor M. Lubecke, "Separation of Respiratory Signatures for Multiple Subjects Using Independent Component Analysis with the JADE Algorithm," *40th Annual International Conference of IEEE Engineering in Medicine and Biology Society EMBC,* 17-22 July,2018.

[9] Simon S. Haykin, "Adaptive Filter Theory", Englewood Cliffs, N. J: Prentice-Hall, 1986.

[10] Shekh Md Mahmudul Islam, Md Salahuddin Farid and Md Adnan Kiber, "Denoising ECG signal using adaptive filter algorithms and cubic spline interpolation for regaining missing data points of ECG in telecardiology system", *International Journal of Enhanced Research in Science, Technology and Engineering,* vol. 4 (12), December, 2015.

[11] Shekh Md Mahmudul Islam and Md Salahuddin Farid, "Denoising EEG signal using adaptive filter algorithms", *International Journal of Enhanced Research in Science, Technology and Engineering,* vol. 4 (11), November 2015.

[12] Md Salahuddin Farid and Shekh Md Mahmudul Islam, "Removal of power line interference from ECG signal using different adaptive filter algorithms and cubic spline interpolation for missing data points of EGC in telecardiology system", *Engineering Technology Open Access Journal,* ETOAJ MS ID: 55555 (2018).

[13] Shekh Md Mahmudul Islam, Abraham Sylvester, Brandon Tomota and Victor M. Lubecke, "A programable robotic phantom to simulate the dynamic respiratory motions for continuous identity authentication," *IEEE Asia Pacific Microwave Conference (APMC'19),* Singapore, 10-13 December,2019.