UAV Radar Sensing of Respiratory Variations for COVID-Type Disorders

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***Abstract*— Unmanned Aerial Vehicles (UAVs) with onboard Doppler radar sensors can be used for health reconnaissance including the remote detection of respiratory patterns associated with COVID-19. While respiratory diagnostics have been demonstrated with radar, the motion of the airborne introduces motion interference. An adaptive filter method is applied here which uses a second radar facing a non-moving surface (ceiling) for a nose cancellation reference signal. Variations in respiratory rate and displacement have been demonstrated which is consistent with the need for detecting tachypnea associated with COVID-19.**

Keywords*— *Doppler radar, triage, adaptive filter, COVID-19, respiration

I. Introduction

With modern advances in technology, unmanned aerial vehicles (UAVs), commonly referred to as drones, have become increasingly accessible and applicable for reconnaissance and triage [1]. Commercially available UAVs can travel anywhere a person can and beyond, only limited by communications range and battery life, and can relay triage relevant information to safely-isolated human responders via optical imagery. While the efficacy of UAV enhanced triage has been supported in several investigations [2] these studies were carried out under optimal visibility. UAV-borne radar motion sensors could potentially enhance reconnaissance capability as radar can detect respiration and heart rates in the dark, through smoke, and through loose clothing [3]. Furthermore, accurate radar tracking of cardiopulmonary activity can provide a sensitive measure of health suitable for diagnostic screening of subjects that may have respiratory disorders such as COVID-19.

The use of radar to sense respiratory variations has been well established, including measurements of respiratory sinus arrhythmia (RSA) and tidal volume, as well as the recognition of obstructive sleep apnea events [4-7]. Furthermore, radar measurements of respiration have been successfully demonstrated for authentication of the identity of an individual from a group [8]. Respiratory patterns associated with COVID-19 are considered to be generally distinct from those associated with flu or the common cold with many infected persons exhibiting Tachypnea [9]. While normal breathing involves rates of about 12 breaths/min and chest displacement on the order of 1 cm, COIVID-19 related rates can be 20-30 breaths/min with chest displacements of 0.5 cm or less. While radar respiratory measurements are straight forward for stationary systems, UAV-based radar systems must compensate for interference imposed by the motion of the UAV on the measurement of desired subject motion.

Earlier research [10] utilized a second radar to measure drone movement and stabilize UAV motion through error feedback. This method requires access to drone flight control which is not typically available in commercial systems. Another study [11] used empirical mode decomposition to distinguish radar movement from the cardiopulmonary movement in the radar signal, relying on foreknowledge of the discerning characteristics of both the desired and noise signals. Thus, if the signals are slightly different than expected, accuracy is reduced, as it would also be reduced in a real-time implementation which is a necessity in triage.

II. Theory

A. Doppler Radar for Physiological Sensing

Despite these shortcomings, the studies strongly indicate that with an accurate reference for the characteristics of the noise, obtained in real-time with the use of a second radar, the respiratory signal could be accurately reconstructed. Recently, an adaptive filter method was applied to compensate for experimentally simulated UAV-platform motion while successfully extracting the respiratory rate of a phantom mover [12-13]. In this study the efficacy of an adaptive filter approach is examined for tracking both the respiratory rate and respiratory displacement variations associated with COVID-19, as illustrated in Fig. 1. An RLS adaptive filter is applied to data from experiments with a robotic respiration phantom measured by a radar supported by a robotic shaker, and respiration rate variations rates from 0.2Hz to 0.5Hz were accurately recognized as well as displacement variations of

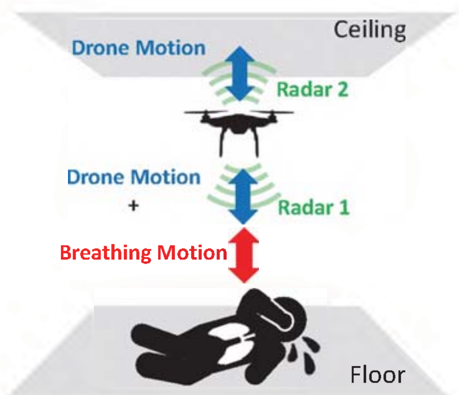


Fig. 1. Indoor drone radar concept for search and rescue operation and it can also be used in hospital environment. Radar 1 is attached to the drone for measuring drone motion and breathing motion while Radar 2 (attached to the ceiling) measures only drone motion. From [12]

3.75, 5.0 and 10mm. Resolution of these variations is on the order of 0.1hz and 1mm or better.

B. Theory of Doppler Radar for Physiological SensingRadar

A typical continuous wave (CW) Doppler radar transmits an electromagnetic signal towards a human target continuously. When the signal is reflected, the phase change of the signal occurs directly proportional to the movement of the chest surface due to cardio-respiratory activities [3]. In a stationary CW radar platform, clutter can be detected only as a DC offset [12]. However, in UAV radar respiration sensing, the platform itself creates motion artifacts. The combined motion is detected by the radar sensor in a UAV platform is [12]:

$$S_{composite}(t) = \cos\left(\frac{4\pi A}{\lambda}\sin(\omega_1 t) + \frac{4\pi B}{\lambda}\sin(\omega_2 t)\right), \quad (1)$$

Where, ω_1 is the angular frequency for the tiny movement of the chest surface and ω_2 is the undesired platform motion that must be suppressed to extract respiratory information. The indoor drone radar concept is shown in Fig. 1. The proposed system can also be employed in a hospital environment by pointing secondary radar at the ceiling or the floor, but an angle of view outside of the radar.

C. Adaptive Filters

An Adaptive noise canceller (ANC) is a popular technique mostly employed in the dual-microphone noise-canceling system [13]. Generally, it receives a noise corrupted signal and independent noise signal as an input. The output of the ANC system is represented as:

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

$$s'^2 = s^2 + (n - n')^2 + 2s(n - n'). \quad (3)$$

Here, the noise, input n_0, passes through a filter to produce an output n'. Taking ensemble average on both sides and assuming that s is uncorrelated with n_0 *and* n' we have:

$$E[s'^2] = E[s^2] + E[(n - n')^2] + 2E[s(n - n')] \quad (4)$$

$$= E[s^2] + E[(n - n')^2]\,. \quad (5)$$

Fundamentally, the goal of the adaptive filter is to minimize $E[s'^2]$ as signal power $E[s^2]$ will be unaffected by adjusting different filter coefficients. There are different popular algorithms in, among them least mean square (LMS) and recursive least square (RLS) is mostly used [14]. The LMS filter tries to adapt its coefficient at one iteration. On the other hand, RLS recursively finds the filter coefficients that minimize the linear least square function of the input signal [14]. In this work, we employed the RLS technique as in our prior attempt it outperformed with LMS for motion compensation [12].

III. Experiemnt and Data

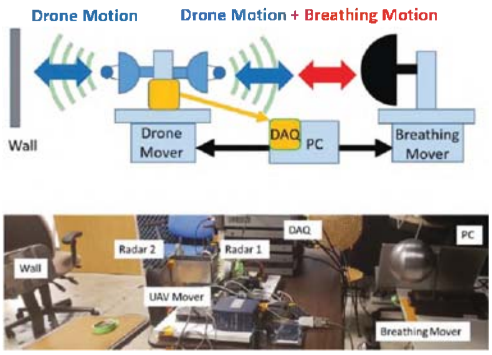


Fig. 2. Simulated drone and mechanical breather, with two radars. Note Radar 2 is pointed towards a reference surface to gather noise for the adaptive filter.

Two 24GHz-KLC-1LP monopulse radar modules were used, each with two channels (I, Q) and connected to Low Noise Amplifiers (LNA) SR560. The LNAs were AC-coupled with a gain of 500 and low-pass filtered with a cut-off frequency of 3 Hz. The LNA outputs were connected to a NI DAQ which connected to the computer through a USB interface. Finally, a customized MATLAB recording interface was used to record the signals. The two radar modules were mounted on a linear actuator, with one pointing towards the simulated breather, and the other to a reference surface, simulating indoor overhead cover. Fig. 2 represents the setup.

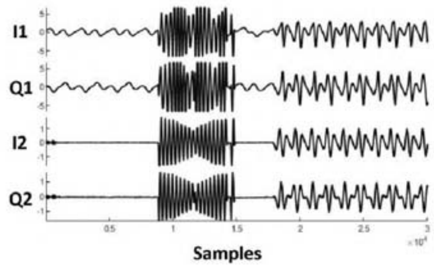
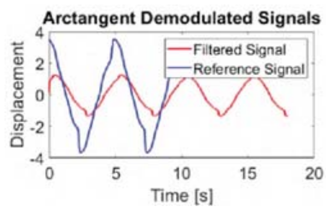


Fig. 3. Raw data capture from DAQ before any filtering or processing for Radar 1 and 2, each with I and Q channel. Note zero drone movement, followed by initialization and then sinusoidal drone movement.

Each recording consisted of thirty seconds of reference data with only the phantom breather moving, followed by the initialization of the simulated UAV movement (Fig. 3). The sampling rate was 500Hz, with a range of -10 to 10V.



a.

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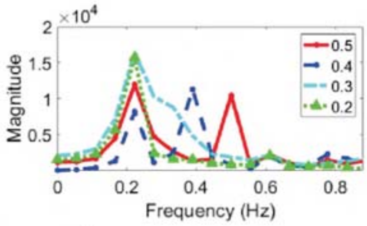
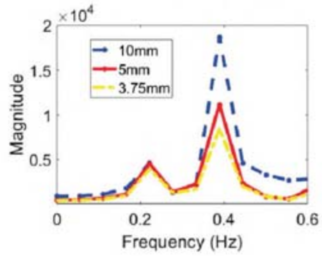


b.



c.

Fig. 4a. Frequency sweep plot from 0.2Hz to 0.5Hz with phantom breather displacement of 5mm. Note interference of noise signal at 0.2Hz makes detection at 0.3Hz unclear.
Fig. 4b. Amplitude sweep at 0.4Hz. Note Corresponding peak reduction for decreased mover displacement.
Fig 4c. Demodulated and filtered signal from Radar 2 compared to the reference measurement. Notice slight variations due to noise signals still present.

To determine if the system is capable of distinguishing variations in breathing rate and depth necessary to detect the changes that occur in patients with COVID-19, fifteen trials were conducted. Breathing was simulated as a sinusoidal pattern with frequency varied between 0.1 and 0.5 Hz in increments of 0.1Hz. Three breathing depths were selected: 3.75, 5, 10mm. The motion of the drone was simulated as a sinusoid with a frequency of 0.2Hz and an amplitude of 10mm peak-to-peak. To account for DC drift, the low-noise amplifiers (LNAs) were operated in AC-coupling mode, and samples were centered on the y-axis using a mean-subtraction method. An RLS filter with an order of 32 was used. Fig. 4a illustrates the reconstructed signal for a reference respiration signal, measured by the system. The reference signal was measured using the same system, with no simulated drone motion. Then a motion was induced, and the RLS filter reduced noise from the motion of the drone. It was assumed that the motion of the breathing simulator is repeatable enough to serve as a reference signal to compare the filtered signal against for accuracy purposes. Fig 4b shows the result of the trials for a breathing depth of 5mm, with distinct peaks present at each corresponding frequency. However, there is still a peak at 0.2Hz corresponding with the motion from the simulated drone movement that has not been completely filtered. Fig 4c. illustrates the ability to distinguish varying breathing depths.

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

With an average calculated error of 86% in the frequency domain, the system is capable of accurately determining frequency within 0.1Hz and amplitude within 0.1mm. Further work should be done to vary the noise motion to include more random and realistic noise and developing a wireless data acquisition system to collect data from a radar system flying on a UAV. Detection in this exploratory work is limited at lower frequencies by the choice of ac-coupling with a high-pass filter. If the noise is significantly higher than the breather amplitude, the peak is still detected, but is not the primary peak. A dc-coupled system is more complicated to implement but would mitigate low frequency distortion.

IV. Conclusion

UAV detection of respiratory disorders is dependent on the ability to detect slight variations in frequency and amplitude that distinguish healthy from distressed breathing. Motion compensation algorithms, such as the RLS algorithm, suppress simulated noise, but only to a certain extent. If the noise is within 0.1Hz and on the same order as the signal, distinguishing the two is difficult, but not impossible. In realistic scenarios, it is unlikely that drone motion signal will be periodic and persist in the same frequency range as the breathing signal. The rapid, and shallow breathing that is typically indicated in COVID-19 patients is detectable and distinguishable in a simulated environment. Further testing on a flying drone should prove the robustness of the RLS algorithm when faced with real flight motion.

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