

# Robust Doppler radar demodulation via compressed sensing

W. Xu, C. Gu, C. Li and M. Sarrafzadeh

The microwave Doppler radar sensor enables a non-contact approach for measuring movement in various applications. One of the most challenging issues is radar signal demodulation because it requires accurate DC offset compensation. Existing works either require a complicated setup procedure or are sensitive to environmental changes. In this reported work, a compressed sensing based approach to effectively demodulate a radar signal is discussed. Through  $\ell_1$  minimisation, the proposed method can reliably demodulate noisy signals with large measurement residuals. To validate the algorithm, three sets of experiments were run to evaluate the demodulation performance. Experimental results show that the proposed method is promising in both simulation and real-case studies.

**Introduction:** Microwave radar is an important remote sensing technology. In recent years, it has been widely applied in various domains including instrumentation, geology and healthcare. Among diverse radar designs, Doppler radar with a quadrature (I/Q) homodyne architecture technique is commonly used owing to the avoidance of the 'null' point issue and the benefit of the range correlation effect. However, Doppler radar suffers from challenges in the arctangent demodulation method, which requires accurate DC offset compensation [1]. The DC offset comes from reflections from stationary objects and circuit imperfections such as the self-mixing effect of the mixer. Therefore, DC offset values are unpredictable and their compensation is challenging. There are some existing works on DC offset compensation in Doppler radars [1, 2]. However, these methods are either inaccurate or sensitive to environmental changes. In this Letter, we present a novel DC offset compensation algorithm for accurate Doppler radar demodulation. Differing from existing methods, our algorithm is based on *compressed sensing* ( $\ell_1$  minimisation), which is an effective robust technique towards large interference.

**Doppler radar sensor:** Fig. 1a shows the system structure of traditional Doppler radar sensors. There are three layers in the system: the RF layer (transmitter and receiver), the baseband layer (signal amplification and ADC) and the digital signal layer (demodulation). Fig. 1b shows the prototype of our radar sensor system. Doppler radar transmits a single-tone signal  $S(t)$ :

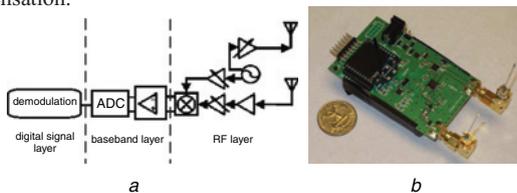
$$S(t) = A_0 \cos(2\pi ft + \phi(t)) \quad (1)$$

where  $f$  is the oscillation frequency,  $t$  is the elapsed time, and  $\phi(t)$  is the phase noise of the oscillator. The received I/Q signals at the radar quadrature mixer output are:

$$B_I(t) = A_I \cos\left[\frac{4\pi x(t)}{\lambda} + \Delta\phi\right] + DC_I \quad (2)$$

$$B_Q(t) = A_Q \sin\left[\frac{4\pi x(t)}{\lambda} + \Delta\phi\right] + DC_Q \quad (3)$$

where  $A_I$  and  $A_Q$  are the amplitudes in channel I and channel Q,  $\Delta\phi$  represents the phase shift of propagation and system phase noise.  $DC_I$  and  $DC_Q$  are DC offset values in I/Q channels, respectively.  $4\pi x(t)/\lambda$  is the phase where the target movement information is modulated, in which  $x(t)$  is the target displacement information. In the baseband layer,  $B_I(t)$  and  $B_Q(t)$  are boosted by a baseband amplifier and then quantified by an analogue-to-digital converter (ADC). Radar data demodulation is performed in the digital signal layer. In this Letter, we neglect the amplitude mismatch in the quadrature mixer and focus on DC offset compensation.



**Fig. 1** Example of Doppler radar structure and prototype  
a Radar structure  
b Radar prototype

To demodulate  $x(t)$ , we calculate DC offset values, ( $DC_I, DC_Q$ ), in I/Q channels such that:

$$R_I(t) = \frac{B_I - DC_I}{A} = \cos\left[\frac{4\pi x(t)}{\lambda} + \Delta\phi\right] \quad (4)$$

$$R_Q(t) = \frac{B_Q - DC_Q}{A} = \sin\left[\frac{4\pi x(t)}{\lambda} + \Delta\phi\right] \quad (5)$$

In this way, the displacement information  $x(t)$  can be extracted by an arctangent function:

$$\Psi(t) = \arctan \frac{R_I(t)}{R_Q(t)} = \frac{4\pi x(t)}{\lambda} + \Delta\phi \quad (6)$$

Because  $\Delta\phi$  is constant, the movement  $x(t)$  is linearly proportional to the demodulated result  $\Psi(t)$ . We can see that accurate DC compensation with ( $DC_I, DC_Q, A$ ) is pivotal in Doppler radar demodulation. With respect to the fact that  $R_I^2 + R_Q^2 = 1$ , DC offset compensation can be formulated into a circle fitting problem stated as follows.

**Formulation 1: (circle fitting)** Given a set of {I/Q} quadrature measurements  $\langle B_I(1:n), B_Q(1:n) \rangle = \{(I_1, Q_1), (I_2, Q_2), \dots, (I_n, Q_n)\}$ , there is a tuple  $(a, b, r)$  such as

$$\min \sum_1^n \|d_i\|_2^2 \quad (7)$$

where

$$d_i = \sqrt{(I_i - a)^2 + (Q_i - b)^2} - r \quad (8)$$

$a, b, r \in \mathbb{R}$

Note that  $d_i$  represents the fitting residual between the measurement  $(I_i, Q_i)$  and the circle  $(a, b, r)$ .

**Proposed algorithm:** The circle fitting problem has been studied intensively in the past decades. The original form in *Formulation 1* is non-convex and cannot be solved effectively. The state-of-the-art method for this problem is to relax the calculation of residual  $d_i$  to:

$$d_i = (I_i - a)^2 + (I_i - b)^2 - r^2 \quad (9)$$

With (7) and (9), the radar demodulation can be reformulated to an  $\ell_2$  minimisation problem:

$$\min \|Ax - b\|_{\ell_2} \quad (10)$$

where

$$A = \begin{bmatrix} 2I_1 & 2Q_1 & 1 \\ 2I_2 & 2Q_2 & 1 \\ \vdots & \vdots & \vdots \\ 2I_n & 2Q_n & 1 \end{bmatrix}, x = \begin{bmatrix} a \\ b \\ r^2 - a^2 - b^2 \end{bmatrix}, b = \begin{bmatrix} I_1^2 + Q_1^2 \\ I_2^2 + Q_2^2 \\ \vdots \\ I_n^2 + Q_n^2 \end{bmatrix} \quad (11)$$

It is well-known that (10) ( $\ell_2$  minimisation) is an over-determined system and can be solved efficiently. However, this method is quite sensitive to outliers with large residuals because  $\ell_2$  always blindly considers all measurements including outliers. When outliers in measurement appear (such as huge noise or errors),  $\ell_2$ -based demodulation results will be off from the optimal solution.

In this Letter, we attempt to tackle the above issue for robust demodulation results. Assuming that most of the measurements are accurate, and outlier numbers are comparably not large, we can use the following form to guide the demodulation procedure:

$$\min \|Ax - b\|_{\ell_0} \quad (12)$$

Equation (12) is  $\ell_0$  minimisation, which explores the fitting circle  $(a, b, r)$  that has the maximal number of perfect matching points (i.e. zero-residual points). In other words, this heuristic is to optimise the *sparsity*

of fitting residuals. It works because it has been proved that *sparsity pursuit* (i.e.  $\ell_0$  minimisation) is robust to outliers in fitting problems [3].  $\ell_0$  minimisation is intractable because it is an NP-hard problem. However, it is proved that the solution in (12) is highly probabilistically the same to  $\ell_1$  minimisation. Therefore, the radar demodulation problem can be formulated as follows:

$$\min \|Ax - b\|_{\ell_1} \quad (13)$$

Since (13) belongs to the class of linear programming problems, radar demodulation is well-posed and can be solved in polynomial time.

*Experiments:* We evaluated the performance of the proposed algorithm in three experiments. The first is using the synthesis testbench demodulation. The testbench consists of two parts. One part is the sample points on a unit circle, denoted as *clean data*; the other is random points distributed around the unit circle with large offset, denoted as *noisy data*. As shown in Figs. 2a and b, the green squares represent *clean data*, and the red asterisks represent *noisy data*. We can see that clean data are exactly on an arc track, and noisy data distribute around the arc. We can set the ratio number of clean data and noisy data (RCN) with different values. We evaluated the proposed method ( $\ell_1$  minimisation) and the state-of-the-art method ( $\ell_2$  minimisation) on the same testbench. Figs. 2a and b show the demodulation results. We can see that  $\ell_1$  minimisation is robust to the red outliers, and the demodulation result (the black circle) perfectly fits the clean data (see Fig. 2a). In contrast,  $\ell_2$  minimisation is interfered by noisy data, and there is an obvious mismatch between the demodulation result and clean data (see Fig. 2b).

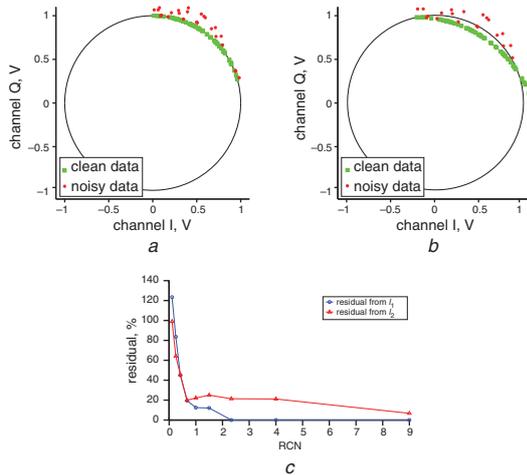


Fig. 2 Demodulation results on synthesis data via  $\ell_1$  and  $\ell_2$

- a Demodulation via  $\ell_1$
- b Demodulation via  $\ell_2$
- c Residual against RCN

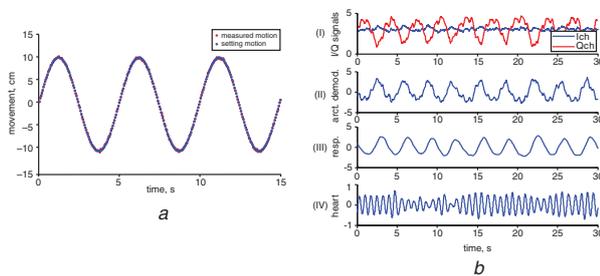


Fig. 3 Fig. 3a is result of sinusoidal motion measurement. Fig. 3b is results of human vital sign detection, where (I) is raw data from I/Q quadrature outputs, (II) is demodulated results with our proposed algorithm, (III) and (IV) are respiration and heart beat after demodulation

- a Motion measurement
- b Vital sign measurement

Furthermore, we investigated the performance with nine different RCNs, changing the value from 0.1 to 9.00. Fig. 2c illustrates residual curves from  $\ell_1$  and  $\ell_2$ , respectively. It shows that  $\ell_1$  minimisation is more robust and has zero residual when RCN is greater than 2.33 (with a ratio of roughly 7:3 between clean data and noisy data). Also, we can see that  $\ell_1$  outperforms  $\ell_2$  when RCN is larger than 0.42 (roughly 3:7), which is the case in most applications. Considering that  $\ell_2$  minimisation is the most used method for Doppler radar demodulation in the literature [2], we believe that our proposed algorithm is an alternative promising approach for robust radar signal demodulation.

The second experiment was to measure the motion of linear actuators. A linear actuator was programmed to perform standard sinusoidal movement with 0.2 Hz and 10 cm amplitude, while the Doppler radar is placed 1.2 m away to measure actuator movements. Fig. 3a shows the demodulation result, where blue dots denote the actual pre-set actuator motion, and red dots denote measured motion of the Doppler radar. As illustrated in Fig. 3a, the measured motion is coherent with the pre-setup motion, and the root mean squared error is less than 1%.

The last experiment was to detect human vital signs. The subject was seated in front of a Doppler radar which measured his chest-wall movement (respiration) and heart motion (heart beat). Fig. 3b shows the demodulated results (respiration in (III) and heart beat in (IV)) close to ground truth from traditional contact medical devices. We performed the experiments with eight subjects, and similar results were observed for all cases.

*Conclusion:* In this Letter, we propose a compressed sensing ( $\ell_1$  minimisation) based approach for accurate radar signal demodulation. We designed three experimental setups for performance evaluation, including one simulated dataset and two actual datasets. Experimental results show our proposed method outperforms state-of-the-art methods in simulation and holds promise in real applications.

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One or more of the Figures in this Letter are available in colour online.

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## References

- 1 Park, B.K., Boric-Lubecke, O., and Lubecke, V.: 'Arctangent demodulation with dc offset compensation in quadrature Doppler radar receiver systems', *IEEE Trans. Microw. Theory Tech.*, 2007, **55**, pp. 1073–1079
- 2 Zakrzewski, M., Raittinen, H., and Vanhala, J.: 'Comparison of center estimation algorithms for heart and respiration monitoring with microwave Doppler radar', *IEEE Sens. J.*, 2012, **12**, pp. 627–634
- 3 Candes, E., Li, X., Ma, Y., and Wright, J.: 'Robust principal component analysis', *J. ACM*, 2011, **19**, pp. 2861–2873