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ENHANCED INDOOR MULTI-TARGET COUNTING BASED ON MICRO-DOPPLER FEATURES WITH 24GHZ RADAR

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ABSTRACT

The benefits demonstrated in smart home and energy-saving applications have sparked considerable interest in non-contact technologies for detecting indoor human presence. In optimizing energy utilization, precise remote assessment of individual count is of paramount importance.However, the presence of multiple human targets in indoor environments poses a challenge for quantity estimation, especially when using a simple one-transmitter-two-receiver 24GHz radar system. Due to limitations in bandwidth and the number of receiving antennas, the system exhibits poor resolution, rendering traditional distance-angle estimation algorithms ineffective in distinguishing targets.To address the indistinguishability issue of multiple targets in the distance-angle domain, we propose a target counting algorithm based on the micro-Doppler domain. Leveraging an atomic norm minimization method, this approach separates target respiratory frequencies and determines the number of targets. Through simulations and practical experiments, our approach demonstrates superior performance in target counting compared to traditional Fourier transform and compressive sensing methods.

Index Terms— Micro-Doppler Domain,Atomic Norm Minimization,24GHz Radar System

1. INTRODUCTION

In recent years, the growing interest in the Internet of Things (IoT) has spurred research into sensors for counting indoor personnel, particularly in the context of remote sensing[1]. The integration of personnel counting information with the IoT holds promise for developing efficient automated systems, enabling adaptive heating or cooling in crowded indoor spaces[2].

While various vision sensor-based solutions have been explored for people counting, these solutions raise privacy concerns and are sensitive to lighting conditions[3]. To address these challenges, there is a shifting focus towards leveraging radar signals for people counting, emphasizing the advantages of radar in remote sensing applications[4]. Radar signals prove advantageous as they are unaffected by lighting conditions, operate robustly in dense fog, and ensure user privacy, making them suitable for private environments like homes and hotels.

In typical scenarios, where multiple human targets move randomly indoors, the separation and counting of these targets can be achieved through distance- or angle-based methods when the spacing between them exceeds the resolution of the radar[5]. However, challenges arise when targets share the same resolution unit.

To overcome this challenge and accurately estimate the number of targets, especially in situations where targets are indistinguishable in both distance and angle, we propose a method based on the micro-Doppler characteristics of targets. Micro-Doppler characteristics, related to the significant phase variations in radar intermediate frequency signals caused by the chest movements of stationary individuals due to breathing, are extracted in the phase domain. Different targets with slightly different breathing frequencies allow us to estimate frequencies from the micro-Doppler information, determining the separated frequency count and consequently, the number of people.

Current methods for extracting human respiratory frequencies, often relying on the Fast Fourier Transform (FFT), face challenges such as insufficient resolution and leakage caused by limited data[6]. To overcome the limitations of FFT, we introduce an atomic norm minimization(ANM) method, proven to have super-resolution capabilities under finite-time measurements[7].

This paper addresses the issue of static targets being indistinguishable in both distance and angle for a 24GHz radar, focusing on separating micro-Doppler characteristics. We propose a millimeter-wave radar people counting method based on phase-domain atomic norm minimization, offering potential applications in remote sensing. The methodology involves constructing the phase-domain received signal, introducing a people counting algorithm based on the atomic norm framework, and validating its effectiveness through

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comprehensive simulation and experimental comparisons with FFT-based methods.

2. METHOD

This section provides a brief introduction to the signal model of a frequency-modulated continuous-wave (FMCW) millimeter-wave radar system used for counting the number of individuals in indoor scenarios. The non-contact FMCW radar represents the intermediate frequency (IF) signal obtained by mixing the transmitted and received signals through a mixer as follows:

$$X_{IF}(t) = Ae^{j(2\pi f_{IF}t+\phi_{IF})}. \tag{1}$$

The phase of the IF signal can be expressed as:

$$\phi_{IF} = \frac{4\pi(X + s(\mathrm{t}))}{\lambda}, \tag{2}$$

where X represents the basic distance between the person and the radar, and s(t) is the displacement caused by the chest movement due to respiration over time. Since the chest movement is in the millimeter range, it has almost no effect on the frequency of the intermediate frequency signal but reflects in the phase change. For a 24GHz millimeter-wave radar with a wavelength $\lambda = 1.25cm$, when the displacement changes by $\Delta s = 1mm$, the phase change is given by 0.32π.The process of extracting the phase information from the target is as follows: Firstly, perform a range-FFT on the radar echo data to obtain a range-time map. Then, use the real and imaginary parts of each range gate signal to extract the phase information.

$$\phi(t) = \arctan(\frac{imag(t)}{real(t)}). \tag{3}$$

Due to the limitation of the arctangent function typically confined to the range -π to π, actual phase values exceeding this interval may encounter phase wrapping phenomena. Therefore, a phase unwrapping operation is necessary. If the difference between the current point and the previous point is greater than π, subtract π from the current point and all subsequent points. Conversely, if the difference is less than π, add π to the current point and all subsequent points. This process ensures the retrieval of accurate phase information. The phase information encapsulates chest movement induced by human respiration.

The chest movement model associated with human respiration is characterized as sinusoidal motion. It is noteworthy that fluctuations caused by heartbeats are far smaller than those caused by respiration and can be safely neglected. The chest oscillations induced by breathing can be modeled by the following equation:

$$s(\mathrm{t}) = A_b \sin(2\pi f_{breath}t), \tag{4}$$

where A_b represents the amplitude caused by respiratory movement, and f_{breath} denotes the respiratory frequency. As multiple targets share the same distance resolution unit, the phase signals overlap with each other. Representing them in complex form and accounting for noise introduced by the environment, the measurement signal can be expressed as follows:

$$Y = \sum_{k=1}^{K} c_k e^{-j(2\pi f_k t+\phi_k)} + N = X + N, \tag{5}$$

where K represents the number of targets, c_k signifies the amplitude of the current target, f_k denotes the respiratory frequency of the current target, ϕ_k stands for the phase, N follows a Gaussian distribution, X represents noise-free measurements, and Y represents measurements with noise. Human respiratory frequencies fall within the range of 0.1Hz-0.8Hz, with amplitudes ranging from 4mm-12mm.

For the received signal Y, the objective is to determine how many frequency components constitute it. This problem can be formulated as finding matching atoms from an infinite continuous dictionary. According to the aforementioned signal form, atoms and the atom set are defined as follows:

$$a(f_k\phi_k) = [1, e^{-j(2\pi f_k t+\phi_k)}, \ldots, e^{-j(2\pi(N-1)f_k t+\phi_k)}]^T \tag{6}$$

$$\mathcal{A} = \{a(f_k\phi_k)|f_k \in [0,1], \phi_k \in [0,2\pi)\}. \tag{7}$$

It can be observed that the received single-channel phase data can be represented as a non-negative linear combination of atoms. This is analogous to sparse representation where received signals can be represented by a non-negative linear combination of atoms from a redundant dictionary. However, unlike the discrete values of atomic parameters in a redundant dictionary, the parameters f_k,$\phi_k$in the atom set are continuously valued in the continuous domain. In this case, the problem of estimating the number of targets can be equivalently viewed as the process of selecting the most sparsely represented signal from a redundant dictionary containing infinitely many atoms. This is akin to directly conducting sparse modeling in the continuous domain, bypassing the steps of grid discretization representation, and the algorithm's performance is no longer affected by arbitrary increases in correlation between atoms in the redundant dictionary.

The denoising problem model based on phase-domain atomic norm minimization, as formulated from the above expression, can be represented as:

$$\hat{X} = \min_X \gamma \parallel X\|_A + \frac{1}{2} \parallel Y - X \parallel_2^2, \gamma = \sigma\sqrt{N \lg N}. \tag{8}$$

The atomic norm of X is expressed as follows:

$$\begin{aligned} \|X\|_{\mathcal{A}} &= \inf\{t > 0 : X \in t\,\mathrm{conv}(\mathcal{A})\} = \inf\{\sum_{k=1}^{K} c_k : \\ X &= \sum_{k=1}^{K} c_k a(f_k\phi_k), c_k \geq 0, f_k \in [0,1], \phi_k \in [0,2\pi)\}. \end{aligned} \tag{9}$$

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The given equation is then transformed into an equivalent semi-definite programming (SDP) form for solution:

$$\min_{X} \gamma\left(\frac{1}{2}t+\frac{1}{2}u_1\right)+\frac{1}{2}\parallel Y-X\parallel_2^2 \tag{10}$$

$$\text{s.t.}\begin{bmatrix} t & X^{\mathrm{H}} \\ X & T(u)\end{bmatrix}\geq 0, \tag{11}$$

where $\parallel Y-X\parallel_2^2$ is the data fitting term, γ is the non-negative regularization coefficient used to balance ensuring both the sparsity of the atomic coefficient vector and the accuracy of the data fitting, t is a free variable introduced to prevent trivial solutions, and X and u are the variables to be optimized, with u_1 being the first element of u. By solving the SDP optimization problem as shown in the equation above, one can obtain the Toeplitz matrix $T(u)$. This matrix can be interpreted as a low-rank, semi-definite array covariance matrix, reconstructed in an optimized manner. It possesses a Vandermonde decomposition in the following form:

$$T(u)=APA^H \tag{12}$$

$$A=[a^T(f_1,\phi_1),a^T(f_2,\phi_2),\ldots,a^T(f_k,\phi_k)] \tag{13}$$

$$P=diag([c_1,c_2,\ldots,c_k]). \tag{14}$$

Due to the one-to-one mapping relationship between the estimated parameter f and $T(u)$, by performing frequency retrieval on $T(u)$, corresponding estimations can be obtained. In this paper, Prony's Method is employed as the frequency retrieval method[8].

3. EXPERIMENTATION AND EVALUATION

In this section, the performance of one-dimensional parameter estimation based on micro-Doppler signals is validated through simulation experiments. To assess the superiority of ANM in estimating the number of targets, a simulation signal is generated based on the multi-target signal model in Equation 5.

For comparison, traditional Fourier Transform, L1-norm-based Compressed Sensing (CS-L1), and Orthogonal Matching Pursuit-based Compressed Sensing(CS-OMP) are employed for target number estimation. A threshold is set at 60% of the maximum amplitude in the spectrum, and frequency points with amplitudes exceeding this threshold are considered as target frequencies. The final step involves counting the number of targets that satisfy the threshold. In Fig.1, the effects of the FFT, CS-L1, CS-OMP, and ANM algorithms on simulated data are presented. The simulation involves two targets with frequencies of 0.27 Hz and 0.3 Hz, a sampling frequency of 10 Hz, a data length of 128, and additive Gaussian noise with a signal-to-noise ratio of 20 dB.

FFT, CS-L1, and CS-OMP reconstruction methods belong to grid-based approaches. For instance, in FFT, the frequency resolution is equal to the sampling frequency divided by the sequence length. Therefore, the FFT frequency resolution is 0.078 Hz for a sequence length of 128. CS employs a Fourier transform basis, and since the target frequency separation of 0.03Hz is less than the resolution, the target separation cannot be achieved. For targets with frequency separations smaller than the grid spacing, traditional methods exhibit reconstruction errors and are unable to distinguish between multiple targets. In contrast, the grid-free coefficient reconstruction method employed by ANM can accurately separate multiple targets with smaller frequency intervals.

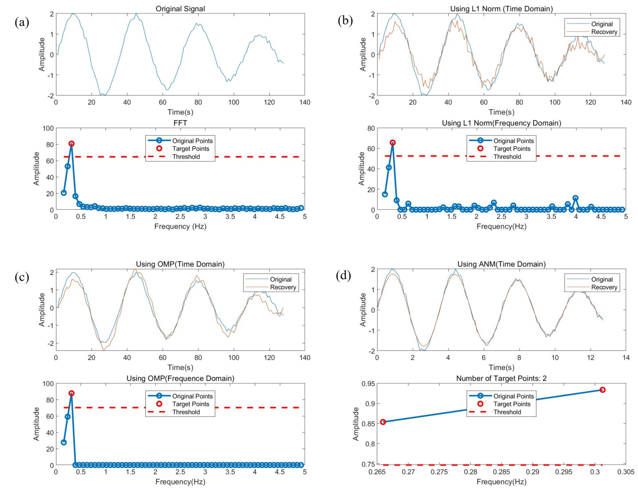

Fig. 1. Comparison of methods. (a) FFT. (b) CS-L1. (c) CS-OMP. (d) Ours.

For the practical experiments, the radar is equipped with one transmitting antenna and two receiving antennas. The carrier frequency is set to 24 GHz, with a bandwidth of 250 MHz. The frame period is set to 32 ms, and there are 1000 chirps per second. The experimental setup is illustrated in Fig.2. In this experimental scenario, the radar is stationary, and the target is positioned facing the radar while remaining stationary. If there are multiple targets, they are seated closely together.

Fig. 2. Experimental scene

Participants are seated at a distance of 3 meters in front

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of the radar. Each participant has a respiratory rate difference of 5 breaths per minute. The number of participants is adjusted, starting from 1 person and gradually increasing to 3 people. Each configuration is tested 10 times. Due to the high dimensionality of the data, the data is down-sampled to obtain 256-point data. FFT is performed on both the original length data and the down-sampled data. Additionally, L1-norm-based CS method, OMP-based CS method, and ANM are employed. Quantity estimation errors are measured using mean square error. The results are illustrated in Fig.3.

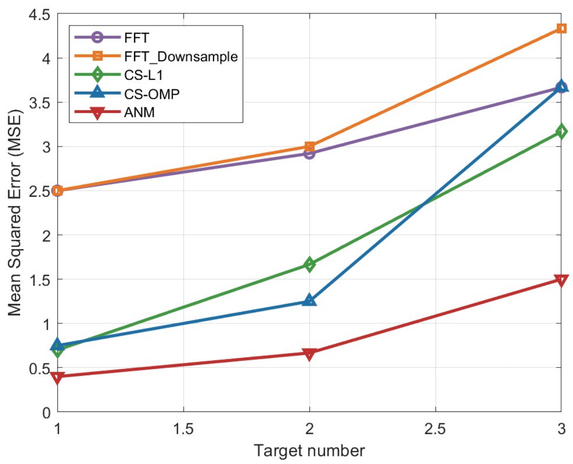

Fig. 3. MSE for target count estimation

It can be observed that, compared to FFT, L1-norm-based CS method, and OMP-based CS method, the proposed model in this paper more accurately estimates the number and position of human targets. The FFT method results in a larger error in the detected target quantity, primarily due to limitations in frequency spectrum resolution and spectrum leakage, leading to significant estimation errors. The two CS methods, relying on Fourier transform bases, essentially still employ grid-based matching methods, facing limitations in grid resolution. This can result in grid mismatch errors when the true frequencies do not fall on the predefined grid, leading to substantial estimation errors.The proposed method in this paper belongs to a grid-free approach, essentially selecting matching atoms in continuous domains. As a result, it offers higher resolution and minimizes errors in target quantity estimation.

4. CONCLUSION

In conclusion, this paper addresses the challenge of estimating the quantity of targets in indoor millimeter-wave radar scenarios, particularly when dealing with multiple stationary targets that cannot be distinguished in the distance-angle domain. The proposed non-contact target quantity estimation method, based on atomic norm minimization in the phase domain, leverages the frequency differences in the Doppler features of targets. By utilizing an infinite continuous dictionary for frequency matching, the method accurately estimates target quantity even in cases of small frequency differences. Simulations and experiments demonstrate the effectiveness of this approach in estimating target quantity in scenarios with multiple targets, outperforming traditional methods such as FFT, L1-norm-based CS, and OMP-based CS methods.

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