Poster Abstract: Adaptive Chirps Domain Window Order of MM-Wave Radar for UAV Motion Capture

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ABSTRACT

Accurate motion capture of aerial robots in 3D is a key enabler for autonomous operation. Recently, some research considers using MM-Wave radar sensors for drone motion capture. However, due to the high noise and difficulty in capturing the center of an object in MM-Wave radar, the existing traditional methods have achieved unsatisfactory results. We develop a novel adaptive chirps domain window order method for MM-Wave radar data and customize a neural network architecture.

KEYWORDS

Unmanned Aerial Vehicle, MM-Wave Radar, Neural Network

1 INTRODUCTION

In recent years, the rapid evolution of unmanned aerial vehicles (UAVs) has generated a surge in applications ranging [1]-[2]. Studies are focusing on how to efficiently solve the drone scheduling problem [3], and there is research exploring UAVs attitude stabilization schemes using a deep learning-based approach [4]. This paper achieves efficient ground-to-air heterogeneous data communication with attention-based graph reinforcement learning [5].

Recent advancements in MM-Wave radar technology have opened new avenues for drone tracking. Traditional methods, such as optical or ultrawide-band motion capture, often come with limitations such as high cost and complex setup. Unlike optical systems, MM-Wave radar offers a compelling alternative with its ability to operate in diverse conditions. Traditional methods include 2DFFT, Music methods, etc. Recently, the deep learning method is also introduced [6]. However, these method overlook fundamental properties of radar data, i.e., chirps group frame information, resulting in poor effect. To address this shortcoming, we propose a novel method based on a key insight: each group of chirps of sampled radar data corresponds to a time correlation. As shown in Fig.1, the multiple groups of chirps form a window in chirps domain and when we estimating the kth sample S_k of the chirps group data, we also need to simultaneously refer to the data of (S_{k-N}, S_{k+N}) group. When we utilize chirps frame domain windows, we obtain more contextual information, which is then fed into the subsequent neural network for improved prediction accuracy. The window size is defined as order N. However, larger orders will generate redundant information especially in the corner of UAV trajectory. Too few orders will result in missing contextual information especially in the flat trajectory. How to introduce this chirps domain information correctly and determine the order still remains a problem.

Our contributions include:

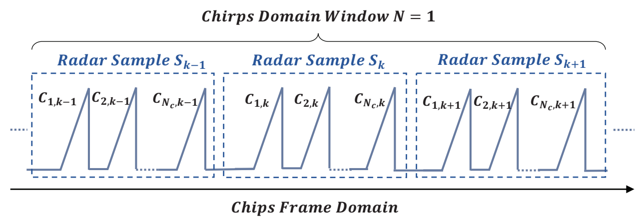

Figure 1: Proposed chirps domain window with order $N = 1$.

Table 1: Comparisons of Different Methods

Method	Error(cm)	Time/Frames(ms)
Point Cloud	36.2	603
2D FFT	80.1	**21**
3D FFT	38.3	723
2D MUSIC	72.5	86477
3D MUSIC	27.6	1312510
mDrones[6]	8.92	262
Proposed Method	**4.4**	161

- The innovative adaptive chirps domain window order extraction algorithm, which introduces the information of chirps domain.
- A novel MM-Wave radar based approach overall pipeline for drone tracking to improve accuracy and response time.

2 OVERVIEW

The overall pipeline we used is shown in Fig.2. We split our system into three types: 1) MM-Wave Data Processing; 2) Adaptive chirps domain windows order extraction; 3) neural network architecture.

2.1 MM-Wave Data Processing

The Frequency-Modulated Continuous Wave (FMCW) radar is used as the source of the radar data. In our pipeline, let the source radar data samples defined as $S_k, k = 1, 2, ..., N_s$, where N_s is the number of radar data. Each sample include multiple chirps, which can be defined as $C_{(t,k)}, t = 1, 2, ..., N_c$ of kth sample, where N_c is the number of chirps. We next use the standard method conventional 2D FFT to obtain N_h heatmaps of multiple groups of chirps of each samples. N_h = 6 heatmaps are calculated from each chirps in our pipeline, i.e., 2 azimuth heatmaps and 4 elevation heatmaps. The heatmaps of t th chirp in k th sample can defined as $H_l^{C_{(t,k)}}, l = 1, 2, ..., N_h$. The heatmap data of x th in the X-axis and y th in the Y-axis can be defined as the sampled function of H as $H(x, y)$.

[*]Both authors contributed equally to this research.

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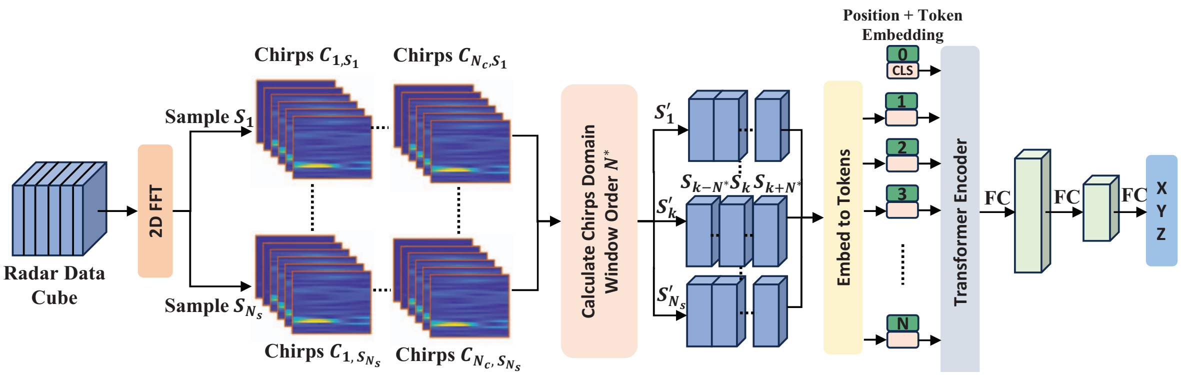

Figure 2: Proposed pipeline.

2.2 Adaptive Chirps Domain Window Order

In this phase, our goal is to obtain the effective minimum order of the time domain window. We propose an algorithm to justify if the present order is enough or not.

Let $\phi(S_a, S_b)$ defined as the total error of all the chirps between sample S_a and S_b as follows:

$$\phi(S_{k_a}, S_{k_b}) = \sum_{t=1}^{N_c-1} \sum_{l=1}^{N_h} \sum_{(x,y)\in(W,L)} \|H_l^{C_{(t+1,k_a)}}(x,y) - H_l^{C_{(t,k_b)}}(x,y)\| \tag{1}$$

where W is the width of heatmap, L is the length of heatmap.

Then we calculate the average error $\varepsilon(N_i, S_k)$ of the N_i order chirps window of the $k\ th$ samples as the center of the window, formulated as

$$\varepsilon(N_i, S_k) = \frac{1}{2} \sum_{k_a=k-N_i}^{k+N_i-1} \|\phi(S_{k_a}, S_{k_a+1})\|^2 \tag{2}$$

We defined N_{min} and N_{max} to limit the order range. At the beginning we set $N_i = N_{min}$. In each iteration, we gradually increase the order N_i to perform the process above (i.e., (1)-(2)). When the iteration is finished, we set $N_k = N_k + 1$ and repeat (1)-(2). Once $N_k = N_{max}$ is satisfied, we compare the error and calculate the order N^* of chirps window. The final order N^* can be formulated as

$$N^* = \underset{N_i \in \{N_{min}, N_{max}\}}{\arg\min} \left\{ \sum_{k=N_i}^{N_s-N_i} \varepsilon(N_i, S_k) \right\} \tag{3}$$

2.3 Neural Network

In the above section, we calculate the chirps domain window order N^*. Subsequently, we assemble the original $k\ th$ sample S_k into new sample $S_k^{'}$ which combine the information of chirps domain, formulated as

$$\mathbf{S}_k^{'} = \begin{bmatrix} \mathbf{S}_{k-N^*} & \mathbf{S}_{k-N^*+1} & \dots & \mathbf{S}_{k+N^*-1} & \mathbf{S}_{k+N^*} \end{bmatrix} \tag{4}$$

Next the radar data $S^{'}$ are embeded into tokens vectors. Transformer is used as our backbone.

3 PERFORMANCE EVALUATION

We implement 6 methods as comparison on the same platform using NVIDIA MX250. The comparison table is shown in Table 1. The average localization error of our method is smaller then the best competing baseline.

4 ACKNOWLEDGMENTS

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