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Event-based radar perception processing

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Abstract — **We consider the problem of the large amount of data produced by current radar systems, particularly Frequency Modulated Continuous Wave (FMCW) radars, with the goal of minimizing latency and memory usage in signal processing pipelines for edge-based applications. Drawing inspiration from event-based cameras, we propose a novel event-based radar perception method that utilizes only two single snapshots to achieve performance levels suitable for current radar applications. After mathematically deriving the approach, we validate its effectiveness through both simulations and real-world experiments involving multiple targets.**

Keywords — **Event-based radar, signal processing, MIMO radar processing.**

I. INTRODUCTION

With the advent of the Internet of Things (IoT) and ubiquitous sensing, a very large amount of data is produced. This implies energy costs for communication & processing, and memory to store such data, often setting a drawback for edge-computation capabilities. Event-based hardware and processing can greatly reduce the amount of data. Examples include Dynamic Visions Sensors [1], which only record changes in an image as discrete polarity events instead of providing a full image at a constant frame rate, event-based audio [2] and touch sensors [3].

Another traditionally frame-based sensor is radar, which allows for the estimation of target distance, velocity and angles. Radar is traditionally used in weather forecasting, air traffic control, surveillance & security [4] and short-range applications such as automotive and human sensing. Its main advantage over other sensors is in its ability to operate in all weather and light conditions and preserve users' privacy. Frequency Modulated Continuous Wave (FMCW) radars can be designed to consume very low power ($<$ 1mW) [5], but their conventional signal processing approaches require high ADC data rates and continuous transmission and processing.

Moreover, a large portion of the ADC data contains potentially redundant data from static elements in the radar beam (i.e. the background environment). By applying neuromorphic principles (i.e., event-based coding) to capture only movement, similar to DVS cameras, the data rate can be greatly reduced. Some research has been conducted on designing event-based radar approaches inspired by neuromorphic principles. Muller et al. in [6] uses a delta operation on the slow-time index and samples with 2-bit quantization, so-called 'event-based radar', proving the effectiveness on gesture classification. Guo in [7] uses an iterative orthogonal matching pursuit (OMP) approach to frequency estimation by time-encoded series. However, this method needs a time-encoder with extremely high rate, which is not practical for current radar.

Inspired by event-based cameras, where each pixel independently responds to changes in brightness as they occur [8], we propose a novel event-based radar perception processing. Pixels in a camera are considered similar to range-angle bins in radar, and changes in brightness are related to changes in phase of the radar signals. The proposed radar processing has two main advantages: first, it has low latency and less memory buffers by using only two chirps to perform spatial & velocity target estimation; second, it aims to save only changes in the information instead of the whole conventional data structure for efficiency. The proposed method has been verified in simulations and experimental data.

The rest of the paper is organized as follows. In Section II, the fundamentals of the proposed method are provided, with signal model, problem formulation, and the proposed approach. The simulation results with ideal point targets and an experimental verification are provided in Section III. Finally, conclusions are drawn in Section IV.

II. FUNDAMENTALS & PROPOSED APPROACH

A. *Signal model*

An FMCW radar with a 1D array with N_a antenna elements for azimuth estimation is considered here. Without losing generality, the omnidirectional antenna pattern is considered for the transmitter and the receiver. The signal received by the radar is the sum of the reflected signals by each scattering point in the field of view. After reception, the signal is mixed with the transmitted signal resulting in the baseband signal (de-chirping process). Conventional radar works in a frame-based approach, hence L_d sequentially transmitted chirps are processed together into a frame to estimate the Doppler frequencies of the scattering points. The received radar signals are discretized with f_s sampling frequency as in the following signal model:

$$\begin{aligned} z(p,b,t) = \sum_{k}^{k_s} \alpha_k \exp[-j2\pi(f_0 \frac{2v_k}{c} Tt + \mu \frac{\gamma_k b}{f_s})] \\ \exp[j2\pi f_0 (\frac{pd}{c} \sin\theta_k)] \end{aligned} \tag{1}$$

The different variables are indicated as follows:

$p = 0, 1, 2, ..., N_a - 1$ is the index of the antenna elements counted from the first antenna element in the azimuth direction;

$b = 0, 1, 2, ..., B_d - 1$ is the sampling index in fast time and $B_d = T_c f_s$ is the maximum number of samples within one chirp;

$t = 0, 1, 2, ..., T_d - 1$ is the slow time index;

T_c is the chirp duration;

k is the scattering point's index;

k_s is the total number of scattering points;

α_k is the constant complex amplitude related to the characteristics of the scattering point k;

f_0 denotes the starting frequency of the chirp;

c is the speed of light;

$d = \frac{\lambda}{2}$ is the space between adjacent antenna elements in the MIMO virtual array, and λ is the wavelength;

θ_k denotes the azimuth angle of the scattering point k;

μ is the frequency modulation rate;

$\gamma_k = \frac{2D_k}{c} \ll T_c$, with D_k being the distance between the antenna and the scattering point k;

v_k is the radial velocity of the scattering point k with respect to the radar line of sight;

T is the pulse repetition time (PRT).

B. Problem formulation

As seen in the signal model, the frame-based approach provides the radar with the ability to perform Doppler frequency estimation (i.e., target velocity estimation, as the radial velocity is proportional to the Doppler frequency), as well as the advantage of coherent processing gain. In addition, such an approach increases the latency of current radar systems and produces a large amount of data. This is especially true for cascaded systems composed of multiple MIMO radar chips, increasingly used to improve the achievable angular resolution. Take as an example the cascaded radar by Texas Instrument (TI) [9]. This radar usually operates with 10 frames per second, meaning a total of $10 * 2 * n * B_d * L_d * N_a$ bit/s data is generated, where n is usually equal to 8 for 8-bit quantization, and the '2' comes from considering both real and imaginary data. This number can reach 1Gb/s without using advanced data compression methods. The considered research problem is therefore how to keep radar functionalities while reducing the amount of data to a more manageable level for low-power and edge-computation contexts.

C. Proposed approach

Inspired by event-based cameras, more efficient and compact processing can be achieved by only focusing on the difference between two snapshots. The $t_1 - th$ snapshot of radar signal z_t can be derived from the signal model in (1) as $z_{t_1} = z(p, b, t_1)$. Similar to cameras, which directly measure the brightness of targets spatially by the value of each pixel, an FFT can be first implemented along the fast-time and antenna directions, to separate the targets in range and azimuth. The signal z_{t_1} of one scatterer after FFT (also known as point spread function) is in equation (2). f_p, f_b denote the frequency grids in azimuth and range dimensions, and a_k is the constant denoting the magnitude and FFT gain for the k target.

$$\begin{aligned} Z_{t_1}(f_p, f_b, k) &= a_k \text{sinc}\left(\frac{f_b B_d + \mu\gamma_k T_c}{2}\right) \\ &\text{sinc}\left(\frac{(f_p + \frac{f_0 d \sin\theta_k}{c})N_a}{2}\right) \exp[-j\pi\left(f_b B_d + \mu\gamma T_c\right)] \\ &\exp[-j\pi\left(f_p + \frac{f_0 d \sin\theta}{c})N_a\right)] \end{aligned} \quad (2)$$

Considering another data snapshot at time instant t_2 after a certain interval from t_1, the Doppler effect will change the frequency of the received signal based on the radial velocity of each target. The discretized point spread function at time t_2 can be written as:

$$Z_{t_2}(f_p, f_b, k) = Z_{t_1}(f_p, f_b, k) \exp[-j2\pi f_0 \frac{2v_k}{c}(t_2 - t_1)] \quad (3)$$

In case of k_s multiple targets, the total received signal will be a superposition of each target's point spread functions.

$$Z_{t_i}(f_p, f_b) = \sum_{k}^{k_s} Z_{t_i}(f_p, f_b, k) \quad (4)$$

Due to the presence of the sinc function in expression (2), the amplitude peak will change according to the range and azimuth angle of targets, which is at the basis of the subsequent detection processing. The phase of the signal consists of three parts. The first two terms are the values fixed for each spatial position, whereas the last one is the phase related to the relative movement of the targets and including the Doppler effect. It is noted that once the spatial frequency is fixed (representing a spatial bin in the range-angle domain), the phase change for this specific position is only related to the targets Doppler velocity.

The proposed approach for event-based radar is formulated based on the findings by comparing the phase in each spatial position, as shown in Fig. 1. This change will basically represent whether the target in that position has changed or not. The difference between the phases of a certain spatial position at time t_1 and t_2 in Fig. 1 will be denoted by:

$$p = -4\pi(\frac{v_o f_0}{c}(t_1 - t_2)) \quad (5)$$

where v_o is the radial velocity of targets in the selected spatial bin.

III. RESULTS

The proposed method has been verified based on numerical simulations and experimental tests as follows.

A. Numerical Simulations

In this simulation, we use for simplicity a 1D array radar with 1×86 elements for azimuth DOA estimation, comparable to commercial mm-wave modules operating at 77 GHz [9]. 2D FFT is implemented to separate targets in range and azimuth dimensions.

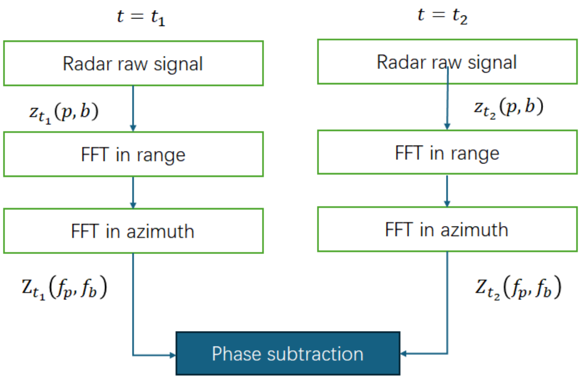

Fig. 1. Processing pipeline for the proposed event-based radar approach.

Table 1. Information for the simulated targets in this study

target	range	azimuth	velocity	reflectivity
1	12.2	-40	-6	240
2	12.2	40	-2	280
3	6.4	38.66	4	145
4	10	38.87	-3	55

The specifications of the radar parameters are listed as follows: the starting frequency of the FMCW chirp f_0 is 77 GHz, the chirp bandwidth B is 640 MHz, the chirp duration T_c is 25.6 μs, the sampling rate f_s is 12 Msps. Four targets are used for the first simulation, with details listed in Table 1. The resulting intensity and Doppler map are shown in Fig. 2 and Fig. 3. The four targets are separated in range-azimuth cells after 2D FFT as expected. From the simulated Doppler map, the Doppler frequency can be estimated for the positions where the four targets exist, proving the effectiveness of the proposed methods.

Another Monte Carlo simulation is implemented with the same settings with different targets Doppler velocities to assess the performances against the signal-to-noise ratio (SNR), as shown in Fig. 4. The SNR is computed after FFT, not directly on the phase. The mean square error (MSE) of estimated velocity drops with a high SNR, as expected. The estimated values reach 0.03 when the SNR=0. The SNR is set from -10 dB to 20 dB. The results show that even with the worse SNR of -10 dB the estimated velocities are still within acceptable ranges of accuracy.

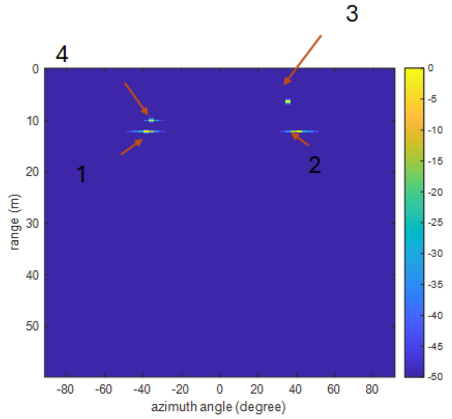

Fig. 2. The intensity map of the four targets in the simulation.

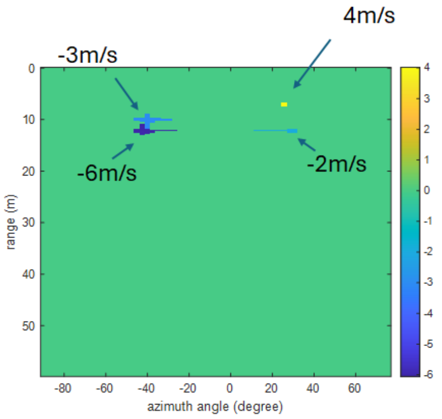

Fig. 3. The Doppler map of the four targets in the simulation, where the image is color-coded with each estimated velocity.

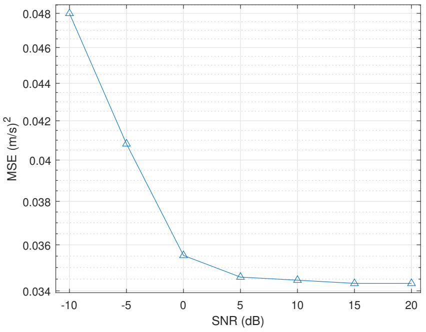

Fig. 4. The MSE of estimated Doppler velocity as a function with SNR.

B. *Experimental tests*

The proposed approach is verified using experimental data collected with the TI MMWCAS-RF-EVM cascade radar AWR2243 [9]. The radar waveform parameters are reported in Table 2. As shown in Fig. 5, the R&S AREG800A automotive radar echo generator is located on the right hand side, with a target simulator connected to generate the simulated target echo with chosen parameters. The TI radar board is located on the right-hand side. Only one target is simulated and set in the range of 29m with Doppler -1.8 m/s.

Since the target simulator is limited to simulating targets in different spatial positions, only one radar channel data is used for processing, and only range FFT is implemented (i.e., no angular FFT is performed). The range profile is shown in Fig. 6, where the detected target at 2.1m is the reflection from the radar target simulator, and the detected target at 29m is the simulated target. Both targets are extracted with the proposed method for estimating their velocity. In the proposed method, only two snapshots are needed for the estimation. Since the radar operates with each frame containing 128 snapshots, all the results for a whole frame are taken here

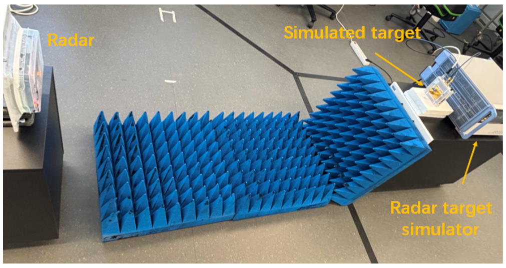

Fig. 5. Experimental setup with radar board and target simulator.

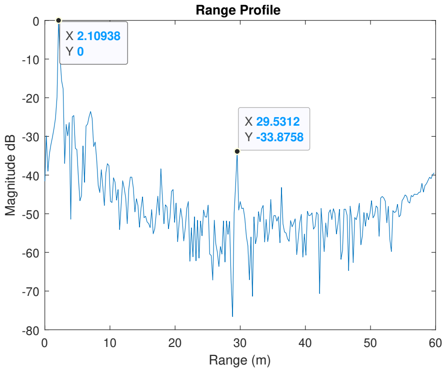

Fig. 6. Example of range profile for the experimental tests.

for statistical analysis. For the real static target, the estimated value is constant as the ground truth of 0m/s, with a small standard deviation of 0.009. However, the simulated target has a mean value of -1.8 m/s as expected, but with a relatively large standard deviation of 0.245. This increased fluctuation level may be attributed to multipath effects in the indoor measurement scenarios, where the range bin at 30 m contains multiple reflected signal components.

IV. CONCLUSION

In this paper, an event-based radar perception processing approach is proposed to reduce data amount while maintaining functionalities. This has two main advantages: it has low latency and less memory buffers by using two chirps to perform spatial and velocity target estimation, and it aims to save changes in the information instead of the whole conventional data structure for efficiency. The proposed method maintains good performances in numerical simulations. When tested with experimental data using an automotive target simulator, promising results have been achieved for static targets, although the results need to be further investigated. In future work, the method will be evaluated in different applications and setups, including with real dynamic targets, and also compared with conventional radar processing.

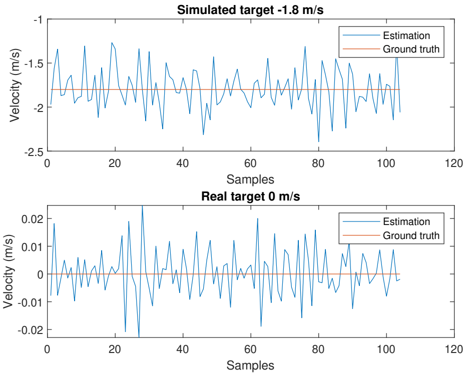

Fig. 7. The estimated velocities for both targets, where the red line indicates the ground truth of those targets.

Table 2. Radar parameters for the experimental data collection

Radar parameters	Symbol	Value
Starting Frequency (GHz)	f_0	79
Chirp Slope (MHz/us)	μ	30
Sampling Rate (Msps)	f_s	12
Bandwidth (GHz)	B	0.64
PRI (ms)	T_c	256

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