Towards Real-Time Implementation for the Pre-Processing of Radar-Based Human Activity Recognition

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***Abstract*—The rapid aging of the population combined with the correlation between age and the increase in falls pushes us to create new ways to monitor the elderly. The privacy of radar data can respond to one of the weaknesses of existing technologies, but the huge amount of radar data to process becomes a challenge to process. We therefore introduce a first architecture allowing the processing of its data in real time. The radar technology used is an off-the-shelf Frequency Modulated Continuous Wave radar Ancortek (SDR 980AD2). It is followed by a pre-processing chain composed of Fast Fourier Transform, Filter and Short Time Fourier Transform to obtain time-velocity maps or spectrograms allowing the extraction of features from gait and human activities. An encouraging implementation (using SIMD logic) on Jetson Xavier allows us to move to data stream processing. Continuous monitoring of the subject will save lives, minimize injuries, reduce anxiety and prevent post-fall syndrome (PDS).**

***Index Terms*—Elderly Fall Detection, Gait analysis, Human Activity Recognition, Radar, Real-Time**

I. Introduction

Nowadays, one global challenge is the rapid aging of the population. With an increasing dependency rate of 2% per year, France and its 1.1 million dependent and precarious people will not have the necessary health infrastructures to face the demographic and epidemiological transformation by 2040 [1]. The various health organizations, such as the World Health Organization (WHO), Santé Publique France (Public Health France), agree on this health hazard and the need to implement an early and targeted screening policy. Keeping elderly people independent for longer at home [2] is essential. Depending on the frailty of the patient [3], a personalized follow-up health course combined with feedback to clinicians has shown a reduction in the rate of falls, including those resulting in injury [4]. Therefore, fall risk should be assessed by estimating frailty and detecting near falls, which are multifactorial [3], [5], [6].

To be able to keep people with loss of autonomy at home for as long as possible and to respond to the policy of early and targeted screening recommended by the WHO, it is necessary to create human activity monitoring systems making it possible to detect and recognize human gait and more particularly falls and its warning signs. To help the patients stay at home, systems must be real-time for a rapid intervention of first responders. Continuous monitoring of the subject will save lives, minimize injuries, reduce anxiety and prevent post-fall syndrome (PDS).

There are many sensors and associated systems in the literature for assisted living. The systems can be classified into different categories, one of the most common system classification being focused on the type of sensor used. They are categorized as follows Vision Based, Ambient Based, Wearables Based. A system that can combine several types of sensors falls into the network of sensors category. The wealth of information of the vision-based systems combined with the democratization of the Kinect which is an affordable, rather efficient and reliable using RGB and Depth (RGBD) technology allowing the posture of a person to be monitored for research in human activity recognition [7]. Wearables, based on inertial units, due to the democratization of smartphones, connected watches and the low cost of these sensors, there are many systems based on this technology [8], [9]. Finally there are ambient-based sensors which provide another mean of non-intrusive fall detection. Sensors such as active infrared, radio frequency identification (RFID), pressure, radar, ultrasonic and/or microphone are used to detect environmental changes due to the fall or activity [10]–[13].

There are several problems/shortcomings with these systems. There is a compromise to be found between the richness of information collected and the perceived privacy of the user [14]. an infrared sensor for example will not be perceived as invading privacy but will provide very coarse information whereas a visible camera will provide very rich information but be perceived as very invasive. Most people nowadays have accepted Wi-Fi routers in their homes. Therefore, the use of RF sensing with radar will be more easily accepted by end users. Additionally, if the data is leaked or hacked, it is not easily interpretable which increases security and reduces privacy concerns further. The radar being able to answer this problem but the quantity of data to be processed is very huge. The real-time detection of abnormal gait requires to implement a parallel software on a heterogeneous architecture.

In this paper we will therefore introduce a radar pre-processing architecture and its implementation on an embedded target, necessary for a future real-time system deployment. This pre-processing block will be integrated into a larger processing chain capable of recognizing and classifying human activity in real time while preserving the privacy of the information.

The rest of this article is organized as follows: The methodology of the architecture and its implementation is described in Section II, followed by some results of the implementation of the architecture with an analysis of these results is given in in Section III. The last section is devoted to the conclusion.

II. Methodology

A. Radar data collection

In this study, the radar is an off-the-shelf Frequency Modulated Continuous Wave (FMCW) system from Ancortek (SDR 980AD2). It is operating in X-band with a carrier frequency of 9.8 GHz, with an instantaneous bandwidth equal to 400 MHz and a chirp duration equal to 1 ms. This yields an unambiguous Doppler frequency range equal to ± 500 Hz, which is sufficient to capture human activities performed indoors. The transmitted power was set to +19 dBm, two receiving antennas and one transmitting antenna were used. The architecture of the radar adopts a hardware dechirping/stretch processing for downconversion. This consists in mixing the received signal with the transmitted signal. The downconverted signal (beat frequency) is then low-pass filtered and amplified before digitization. There are 2 channels in the intermediate frequency after dechirping per receiving antenna one in-phase and the other in quadrature (I/Q) to capture complex samples. The sample rate is 128 per sweep (1ms), so the Analog to Digital Converter (ADC) sampling rate is 128 kHz.

B. Pre-processing

Figure 1 presents the steps for the signal pre-processing chain. The processing starts with reading and reshaping the raw FMCW data in time domain. The raw data are the digitized reflected time-delayed and frequency-shifted signals in complex value before the application of Fast Fourier Transform (FFT) to extract the range information. In this project, the data matrix is reshaped into $128 \times M$ where 128 is the number of time samples per sweep, which is also the size used for the FFT, and M is the number of chirps for an activity record. The FFT is applied to each column of the data matrix (i.e. each single chirp). The beat frequency is proportional to the time travelled by the signal from the transmitter to the target and back to the receiving antenna. The FFT on the raw data provides a range profile for each chirp. Next, a 9^{th}-order high-pass Butterworth notch filter with a cutoff frequency at 0.0075 Hz is used as a moving target indicator to range profile, removing components near the 0 Hz in the frequency domain, which is caused by stationary objects in the environment. Only the range bins of interest from index 5 to 25 (which correspond to 1.875 m to 9.375 m) where the subjects are detected are chosen to reduce the noise for the generation of the time velocity signature or spectrograms. A Short Time Fourier Transform (STFT) using a 0.2 s Hamming window with a 95% overlapping factor is implemented on the acquired range-time data matrix for each range bin in the slow time direction to extract the time-varying micro-Doppler signatures. For FMCW radar systems, the range resolution is proportional to the bandwidth. The Doppler resolution is related to both chirp duration and the number of FFT points used in the STFT. The range resolution is 37.5 cm, and the Doppler resolution is 1.25 Hz (or 0.03 m/s), making it capable of performing accurate velocity analysis and activity classification.

C. Extraction features and further processing

This section describes the proposed approaches for feature extraction, which was not yet implemented but gives some context of the global processing chain, applied to both scenarios of monitoring human activities and gait analysis of specific individuals. For monitoring human activities we extract some features all along the pre-processing chain (from the data matrices) such as: the entropy, the energy curve (mean and variance), the centroid (mean and variance), the bandwidth [15]–[17]. For gait analysis of specific individuals some futher processing from the micro-doppler spectrogram is needed to extract the velocity-time and acceleration-time graph. From where you can extract several useful features (velocity of the the stable phase, step repetition frequency, step length) [11].

D. Target implementation device

To embed the future processing/classification chain into a power efficient yet powerful complete system (Central Processing Unit (CPU) + Graphics Processing Unit (GPU) + Hardware Accelerators), we implemented the pre-processing chain into two different architectures then performed some benchmarks on an Nvidia JETSON TX2 and an Nvidia Jetson Xavier. The main characteristics of the JETSON TX2 are as follows:

- CPU: One HMP (6 cores) including 2 Denver cores (custom core designed by Nvidia to run the ARMv8 ISA) and 4 ARM Cortex A57 cores (to run the ARMv8 ISA). All the cores are compatible with ISA ARMv8 which is the 64-bit architecture of ARM.
- Random Access Memory (RAM): 8 GB L128 bit DDR4 of main memory.
- GPU: A Pascal GPU at 256 CUDA cores (not used in this experiment).
- Operating System (OS) : It runs on L4T (Linux for Tegra, i.e. Linux Kernel 4.9).

The main characteristics of the JETSON Xavier are as follows:

- CPU: One HMP of 4 x 2 cores of Carmel cores (custom core designed by Nvidia to run the ARMv8.2 ISA).
- RAM: 32 GB 256-bit LPDDR4x of main memory.
- GPU: A Volta GPU at 512 CUDA cores (not used in this experiment).
- OS : It runs on L4T (Linux for Tegra, i.e. Linux Kernel 4.9).

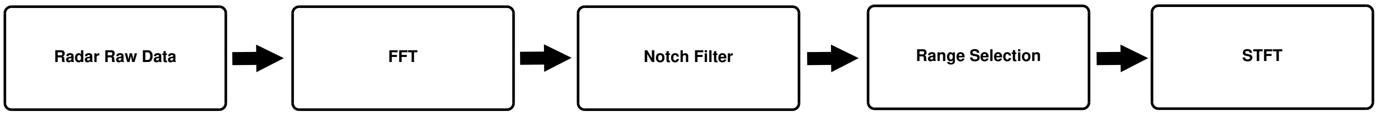

Fig. 1. Pre-processing chain

E. Implementation architecture

As we had to apply the same processing to the data from both receiving antennas (1 & 2), we applied multi-core Single Instruction on Multiple Data (SIMD) logic with OpenMP, after a first phase of extracting and shaping the I/Q radar data, the same processing described in the pre-processing part had been executed, one CPU core (Carmel) per receiving channel. The Discrete Fourier Transforms (DFTs) were performed with the FFTW3 library, the STFT block was custom coded making use of FFTW3 and the implementation of the Butterworth high pass filter was a 9^{th} Butterworth high pass filter for which the coefficients were pre-calculated in Matlab.

III. Results & Discussions

We had to be able to compare processing performances in view of the transition from data packet processing to data stream processing. We chose the execution time as a comparison value in the benchmarks that were performed. Figure 2 depicts the execution time of a 10s activity record for the following benchmarks. All implementations were coded in C++.

The first implementation architecture [A] was a single-core on the Jetson TX2, running the code exclusively on the Denver core (at a frequency of 1.4 GHz). We then ported the implementation to the Jetson Xavier by executing the code on a Carmel core at a frequency of 1.2 GHz [B], we obtain a first step in the acceleration of the code due to the intrinsic architecture of the CPU, the Denver being a 7 Way Superscalar CPU and the Carmel being a 10 Way Superscalar CPU. To continue the acceleration, we increased the operating frequencies of the Jetson TX2 up to 2.0 GHz, by executing the code exclusively on the Denver core [C] and then on the Cortex A57 core [D], we obtain a second step in the acceleration. We then switched to the dual-core OpenMP, since previously, we were sequentially performing the same processing on the data from antenna 1 then on the data from antenna 2. By following an SIMD logic, we went from a processing time of 17.1s time in a single core Carmel [B] to a processing of 9.6s [E]. Finally we increased the operating frequency of the Jetson Xavier up to 2.2 GHz allowing us to reach an execution time of 4.8s on a Carmel core [F] (the maximum frequency of the Jetson Xavier being higher than the Jetson Tx2 due to the engraving technology). We have achieved an acceleration factor of 3.56 compared to our first implementation.

Figure 3 represents the output of the pre-processing chain, it is the micro-Doppler spectrogram with a colorbar indicating the spectrogram amplitudes (calculated by squaring the output matriux after the STFT). From the spectrogram, we will then be able to extract some features as explained in Section II for human activity recognition and/or gait analysis.

TABLE I
Description of the tests

	Platform, number of cores, frequency, platform
A	Denver Nvidia, single core, 1.4 GHz, Jetson TX2
B	Carmel Nvidia, single core, 1.2 GHz, Jetson Xavier
C	Denver Nvidia, single core, 2.0 GHz, Jetson TX2
D	ARM Cortex A57, single core, 2.0 GHz, Jetson TX2
E	Carmel Nvidia, dual core, 1.2 GHz, Jetson Xavier
F	Carmel Nvidia, dual core, 2.2 GHz, Jetson Xavier

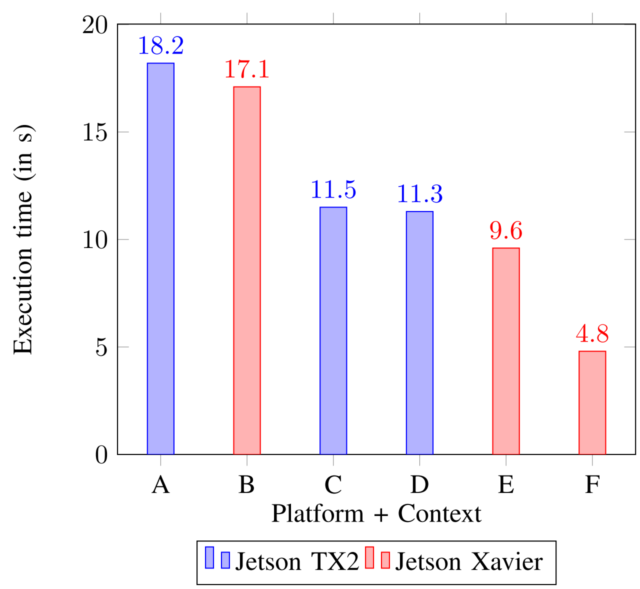

Fig. 2. Processing execution time according to different embedded platforms and different architectures

From the results on both platforms, we have reached a performance level allowing us to move to stream processing architectures. The dual core solution at the frequency of 2.2 GHz on the Carmel CPUs of the Jetson Xavier executes the processing of a 10s radar recording sufficiently quickly which allows us to consider the use of Direct Memory Access (DMA) to manage the acquisition and storage of data in pre-processing buffers. There is still room for improvement in the optimization of the pre-processing chain, such as the use of the GPU for the FFTs, best Cache Memory utilization and organization of the data in memory to further improve performances.

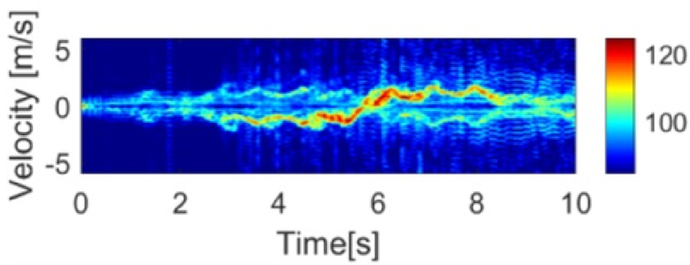

Fig. 3. Micro-Doppler spectrogram of a 10s record

IV. Conclusion

In conclusion, in this article we proposed a embedded implementation of the pre-processing chain before feature extraction towards the real-time classification of fall risk of a person and the detection of falls. We have introduced an architecture (dual core SIMD approach) with timings allowing us to move from data packet architectures to data stream architecture for further implementations. Thanks to these encouraging results, we soon plan to switch the architecture to data flows and introduce the future blocks of the processing chains (feature extractions and classification).

References

[1] N. Blanpain and O. Chardon, "Population projections for 2060: one-third of the population aged over 60," INSEE, 27/10 2010.

[2] H. Aykan, "Report to Congress: Aging Services Technology Study," Washington, 2012.

[3] S. Sourdet, "Recherche des causes de fragilites," in livre blanc - Reperage et maintien de l'autonomie des personnes agees fragiles, B. Vellas Ed. Societe francaise de gerontologie, 2015, pp. 51-53.

[4] A.-M. Hill et al., "Fall rates in hospital rehabilitation units after individualised patient and staff education programmes: a pragmatic, stepped-wedge, cluster-randomised controlled trial", The Lancet, vol. 385, no. 9987, p. 2592-2599, juin 2015, doi: 10.1016/S0140-6736(14)61945-0.

[5] I. L. Kyrdalen, P. Thingstad, L. Sandvik, and H. Ormstad, "Associations between gait speed and well-known fall risk factors among community-dwelling older adults," Physiotherapy Research International, https://doi.org/10.1002/pri.1743 vol. 24, no. 1, p. e1743, 2019/01/01 2019, doi: https://doi.org/10.1002/pri.1743.

[6] K. Nagai et al., "Near falls predict substantial falls in older adults: A prospective cohort study: Near falls predict substantial falls", Geriatr Gerontol Int, vol. 17, no. 10, p. 1477-1480, oct. 2017, doi: 10.1111/ggi.12898.

[7] Y. Xu, J. Chen, Q. Yang, et Q. Guo, "Human Posture Recognition and fall detection Using Kinect V2 Camera", in 2019 Chinese Control Conference (CCC), Guangzhou, China, juill. 2019, p. 8488-8493. doi: 10.23919/ChiCC.2019.8865732.

[8] G. Santos, P. Endo, K. Monteiro, E. Rocha, I. Silva, et T. Lynn, "Accelerometer-Based Human Fall Detection Using Convolutional Neural Networks", Sensors, vol. 19, no. 7, p. 1644, avr. 2019, doi: 10.3390/s19071644.

[9] S. Iloga, A. Bordat, J. Le Kernec and O. Romain, "Human Activity Recognition Based on Acceleration Data From Smartphones Using HMMs," in IEEE Access, vol. 9, pp. 139336-139351, 2021, doi: 10.1109/ACCESS.2021.3117336.

[10] J. Ding et Y. Wang, "A WiFi-Based Smart Home Fall Detection System Using Recurrent Neural Network", IEEE Trans. Consumer Electron., vol. 66, no. 4, p. 308-317, nov. 2020, doi: 10.1109/TCE.2020.3021398.

[11] X. Li, Z. Li, F. Fioranelli, S. Yang, O. Romain, et J. L. Kernec, "Hierarchical Radar Data Analysis for Activity and Personnel Recognition", Remote Sensing, vol. 12, no. 14, p. 2237, juill. 2020, doi: 10.3390/rs12142237.

[12] Z. Liu, M. Yang, Y. Yuan, et K. Y. Kan, "Fall Detection and Personnel Tracking System Using Infrared Array Sensors", IEEE Sensors J., p. 1-1, 2020, doi: 10.1109/JSEN.2020.2988070.

[13] J. Le Kernec et al., "Radar Signal Processing for Sensing in Assisted Living: The Challenges Associated With Real-Time Implementation of Emerging Algorithms," in IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 29-41, July 2019, doi: 10.1109/MSP.2019.2903715.

[14] C. Debes, A. Merentitis, S. Sukhanov, M. Niessen, N. Frangiadakis and A. Bauer, "Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior," in IEEE Signal Processing Magazine, vol. 33, no. 2, pp. 81-94, March 2016, doi: 10.1109/MSP.2015.2503881.

[15] F. Fioranelli and J. Le Kernec, "Radar sensing for human healthcare: challenges and results," 2021 IEEE Sensors, 2021, pp. 1-4, doi: 10.1109/SENSORS47087.2021.9639702.

[16] F. Fioranelli, J. Le Kernec and S. A. Shah, "Radar for Health Care: Recognizing Human Activities and Monitoring Vital Signs," in IEEE Potentials, vol. 38, no. 4, pp. 16-23, July-Aug. 2019, doi: 10.1109/MPOT.2019.2906977.

[17] Gürbüz, Sevgi Zübeyde; Erol, Barış; Çağlıyan, Bahri; Tekeli, Bürkan: 'Operational assessment and adaptive selection of micro-Doppler features', IET Radar, Sonar and Navigation, 2015, 9, (9), p. 1196-1204, DOI: 10.1049/iet-rsn.2015.0144 IET Digital Library, https://digital-library.theiet.org/content/journals/10.1049/iet-rsn.2015.0144