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Reducing Radar Energy Consumption in Classification Tasks through the use of Compressed Sensing

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***Abstract*—In this work we roughly estimate if compressed sensing framework can serve the purpose of energy saving in a frequency modulated continuous wave radar. As a target application we use the classification by neural network. For the particular classification task and different configurations we compare the amount of energy saved by using less ramps, increase in energy consumption induced by extra signal processing and decrease in classification accuracy.**

***Keywords*—compressed sensing; energy saving**

I. Introduction

The core feature of Compressed Sensing (CS) is the ability to recover signals sampling them at the rate lower than the Nyquist rate. The recovered signals have to be sparce or compressible in one domain and spread out in the domain in which they are acquired [1]. Advances in CS algorithms provide means to develop energy efficient solutions in different applications [2-4] using this feature.

There exists a number of approaches to implement CS in radar applications [5]. From an energy saving point of view in case of pulse-Doppler radar CS allows us to reduce the number of pulses per frame. In case of multiple-input multiple-output radar CS enables the decrease in the number of channels. In case of frequency modulated continuous wave (FMCW) radar one can either use the CS-based analog to digital converters (ADCs) [6, 7] or reduce the number of chirps per frame.

Among other advantages, FMCW radars are being implemented either as a single-chip sensor [8] or as a system based on single-chip radio frequency (RF) transceiver [9]. Both implementations have quite low power consumption, especially the former. However, for battery powered radar applications it would be useful to have the minimum possible power dissipation.

The aim of this paper is to roughly estimate whether the amount of energy, which could be saved by sending less ramps, exceeds the amount of energy required to recover the Doppler profiles. We are particularly interested if the recovered profile can be used for the classification purpose and what is the influence of the undersampling on classification performance. As a classification algorithm we use a simple neural network with one hidden layer, which has to decide between two classes. Namely, if the rotating fan is balanced on unbalanced.

The paper is organized as follows. In Section II we describe a target application, which we use as an example. In Section III we estimate complexity of the algorithms and the amount of energy required for calculations. In Section IV we show under which conditions the energy saving is possible. In Section V we analyse the undersampling influence on the classification performance.

II. Classification Task

The target application is the moving objects classification based on their Doppler profiles. In this work we want to make a rough estimation if the energy saving by CS in such an application is possible in principle. Because of that and in order to make reproducible experiments we use a rotating fan with two states: balanced and unbalanced. The fan is unbalanced by a peace of duct tape placed on one of the blades.

The training set consists of the Doppler profiles in the range cell corresponding to the fan distance. The Doppler profiles are measured for both states while the angle between the aperture plane and the plane of rotation equals 0°, ±4° and ±10°. The fan supply voltage for every angle and state is 10V, 12V and 14V.

For the test purpose we use two sets. The first one is collected in the same way as the training set. The second one is collected with the angles equal ±2° and ±6°, and the voltages equal 9V and 11V. Thus the classification of the second test set is a more difficult task, since the data are measured under the conditions that differ from the training ones. The corresponding spectra are shown in Fig. 1. One can notice that the spectra for balanced and unbalanced states and the same fan parameters differ not drastically, but for the same state and different fan parameters the difference in spectra is significant. That makes the classification task challenging.

III. Recovering complexity

Conventional FMCW radar sends a set of equally spaced chirps [8]. This set of chirps is called a chirp frame. The discrete Fourier transform (DFT) of each chirp contains range information. Further it will be called range-DFT. The DFT of each range cell over the chirp frame corresponds to the Doppler profile of the range cell (Doppler-DFT).

If we denote the vector of *i*th range-DFT samples as a complex $\mathbf{y}\in C^M$, where M is the number of chirps per frame, and the Doppler profile in *i*th range cell as $\mathbf{x}\in C^N$, where N is the number of Doppler-DFT samples, then the acquisition of the Doppler profile can be represented as

$$\mathbf{y} = \mathbf{\Phi x},$$

where $\mathbf{\Phi}\in C^{MxN}$. In case $M = N$, $\mathbf{\Phi}$ represents the inverse DFT matrix, that corresponds to the traditional acquisition process with equidistant chirps.

If $\mathbf{x}$ is sparse or compressible, i.e. the Doppler profile has only some nonzero entries or its entries rapidly decay to zero, CS framework allows us to recover $\mathbf{x}$ even when $M << N$ [10]. Thus from an implementation point of view radar have to send M chirps chosen from N equidistant ones uniformly at random; from a mathematical point of view the inverse DFT matrix is reduced to the non-square matrix by choosing M respective rows.

In this work we consider two recovering algorithms: the Basis Pursuit Denoising (BPD) minimizing $||\mathbf{x}||_1$ subject to $||\mathbf{y}-\mathbf{\Phi x}||_2\leq\varepsilon$, where ε is the measurement noise norm, and the Orthogonal Matching Pursuit (OMP). As an implementation of the BPD we use the MATLAB package called l_1-magic.

The complexity of the algorithms can be estimated as the number of floating point operations (FLOPs). As the calculations are made over complex numbers, we take into account that one complex multiplication requires 6 real FLOPs and one complex sum requires 2 real FLOPs.

The range-DFT and the Doppler-DFT can be evaluated by the fast Fourier transform (FFT). Its complexity is given

$$\mathrm{FLOP}_{\mathrm{FFT}} = 2.5n\log_2 n,$$

where n is the number of FFT points.

In order to estimate the BPD complexity we use empirical approach, since the number of iterations during the recovering process can vary. Namely, the number of calls of each line is counted and multiplied by its complexity. In our experiments about 85 percent of the FLOPs fall on solving systems of linear equations during the newton steps.

As an implementation of the OMP algorithm we use LSQR-based one proposed in [11]. The OMP complexity can be estimated analytically. It depends on the initial number of chirps N, the number of sent ramps M and the number of samples to recover S. Thus the OMP complexity is given

$$\mathrm{FLOP}_{\mathrm{OMP}} = S(10N\log_2 N + 16M + 17) +$$

$$+ S(S + 1)(5N\log_2 N + 12M + 67 + 28(2S + 1)/3)/2.$$

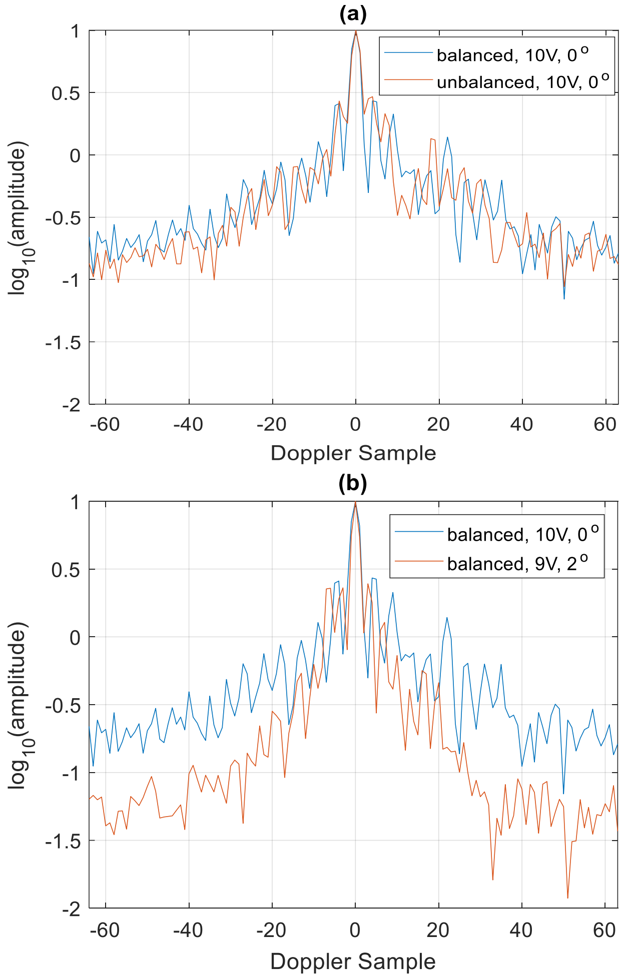

Fig. 1. Typical spectra used in the classification task. (a) – balanced and unbalanced states for the same fan parameters. (b) – both spectra for balanced state, the blue one from training set, the red one from the second test set.

IV. Energy comparison

The energy required to get the Doppler profile E_0 is a sum of the acquisition energy E_a and the processing energy E_p.

The acquisition energy is the energy consumed by a RF-frontend and ADC:

$$E_a = P_a t_a,$$

where P_a and t_a are corresponding power and operating time respectively. The power consumption depends on a number of parameters. Therefore we consider the range of possible values. For example, the claimed power consumption of the modern single-chip sensor from Texas Instrument IWR1443 is 1.73 W with 1 active transmitter and 1.88 W with 2 active transmitters. Thus we assume that reasonable acquisition power lies in the range of 0.1 W to 2 W. The operating time is the product of the chirp duration t_{chirp} and the number of chirps per frame. Hence the acquisition energy per frame is given

$$E_a = M\, P_a t_{chirp}.$$

We assume that the processing energy is the sum of two components:

- The energy consumed while evaluating range-DFTs for M chirps.
- The energy required evaluating Doppler-DFTs in case of conventional radar or the energy required recovering Doppler profiles in case of reduced number of chirps.

The energy required for detection is independent of the number of chirps and is negligible.

The energy required for processing can be evaluated as the algorithm complexity divided by the power efficiency of the processing unit. The power efficiency is measured in the number of FLOPs per second per Watt (FLOPS/W). It depends on the processing unit and the algorithm. Most of the operations are made over vectors, therefore the algorithms can be implemented using a digital signal processor (DSP), a graphics processing units (GPU) or a field-programmable gate array (FPGA). GPUs are power inefficient [12, 13] and are not considered in this work.

In accordance with the power models of the modern C66x DSPs from Texas Instruments their power efficiency lies in the range of 4 to 8 GFLOPS/W. FPGA power efficiency cannot be estimated using claimed peak performance [14]. FPGA power measurements using development boards show 5-6 GFLOPS/W for algorithms such as Cholesky and QRD, and about 10 GFLOPS/W for simpler algorithms such as FFT [13]. In the previous section we mentioned that about 85 percent of FLOPs fall on linear solver, moreover other operations can be partially grouped and evaluated in parallel. Therefore for non-FFT processing we assume the power efficiency of 5 GFLOPS/W, for FFT processing – 10 GFLOPS/W.

Fig. 2–4 exhibit the ratio between the energies required for conventional processing and for the CS-based approach, i.e. the possibility of energy saving. The results for different chirp durations are shown in Fig. 2; for different number of Doppler profiles, i.e. for different number of range cells, in which the classification is carried out – in Fig. 3; for the OMP algorithm with different N – in Fig. 4. The x-axis represents the undersampling factor, i.e. M/N.

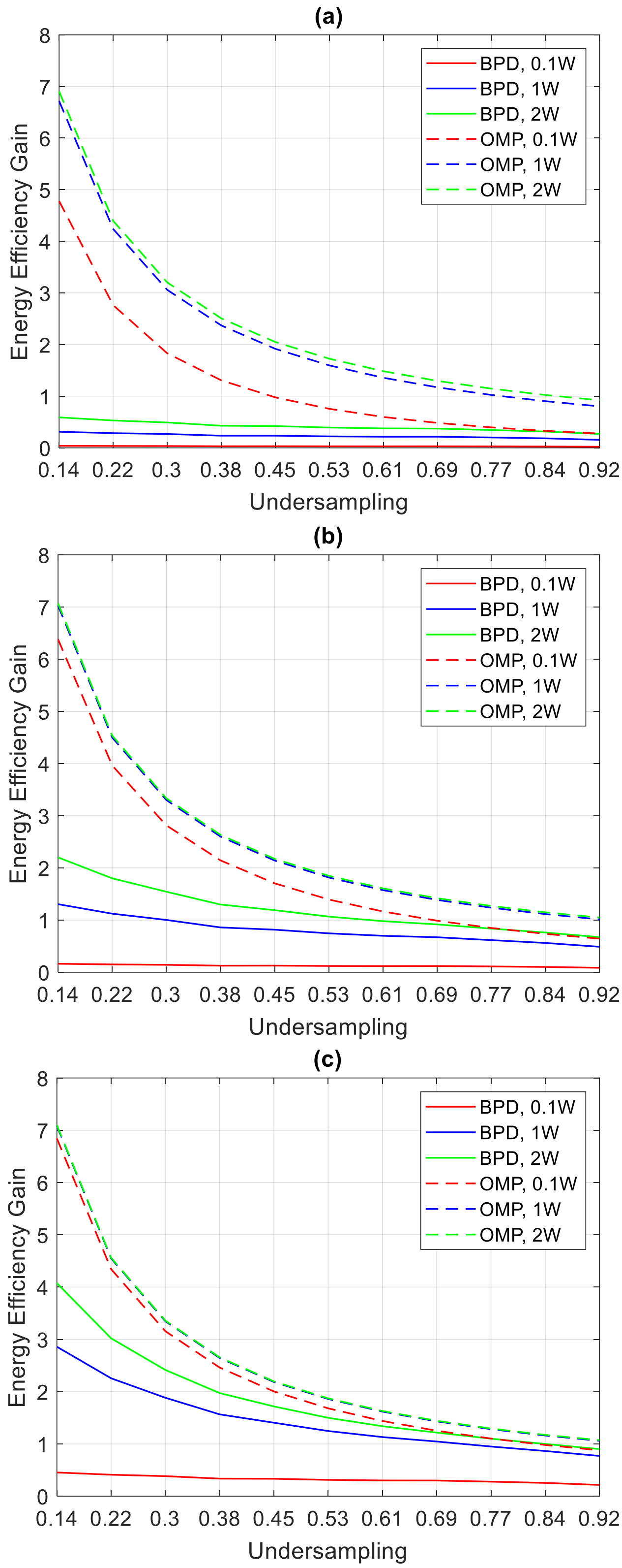

Fig. 2. Energy efficiency gain against the undersampling factor for N=128, one recovered Doppler profile and different algorithm and radar power combinations as indicated in the legend. Chirp durations: (a) – 10 µs, (b) – 50 µs, (c) – 150 µs. The number of recovered samples for the OMP algorithm is M/4.

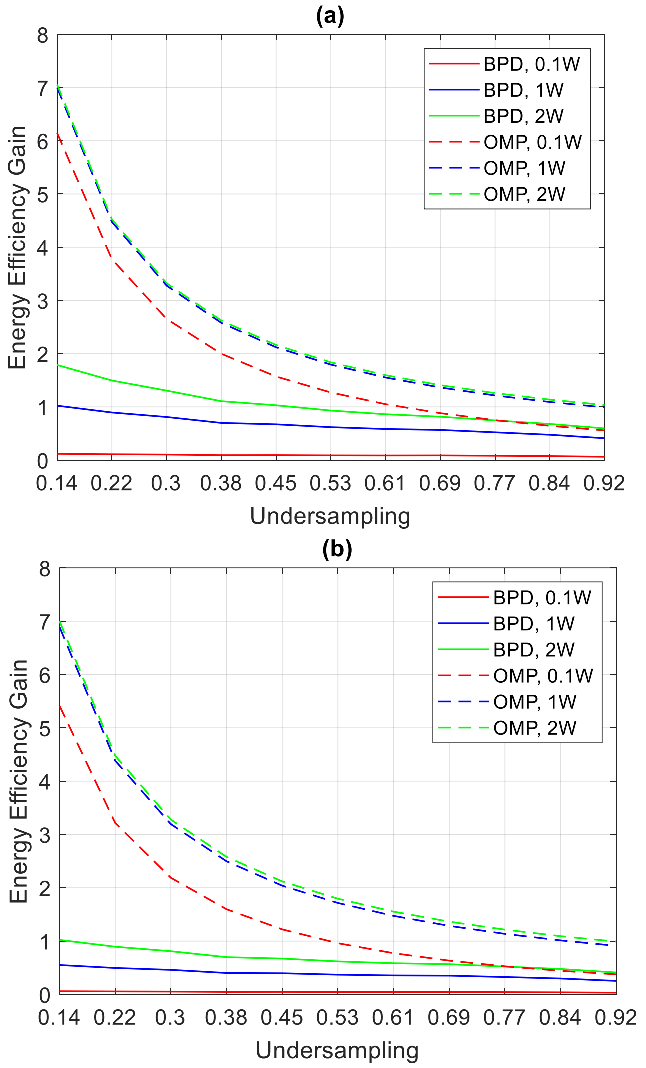

Fig. 3. Energy efficiency gain against the undersampling factor for N=128, chirp duration 150 µs and different algorithm and radar power combinations as indicated in the legend. The number of recovered Doppler profiles: (a) – 4, (b) – 8. The number of recovered samples for the OMP algorithm is M/4.

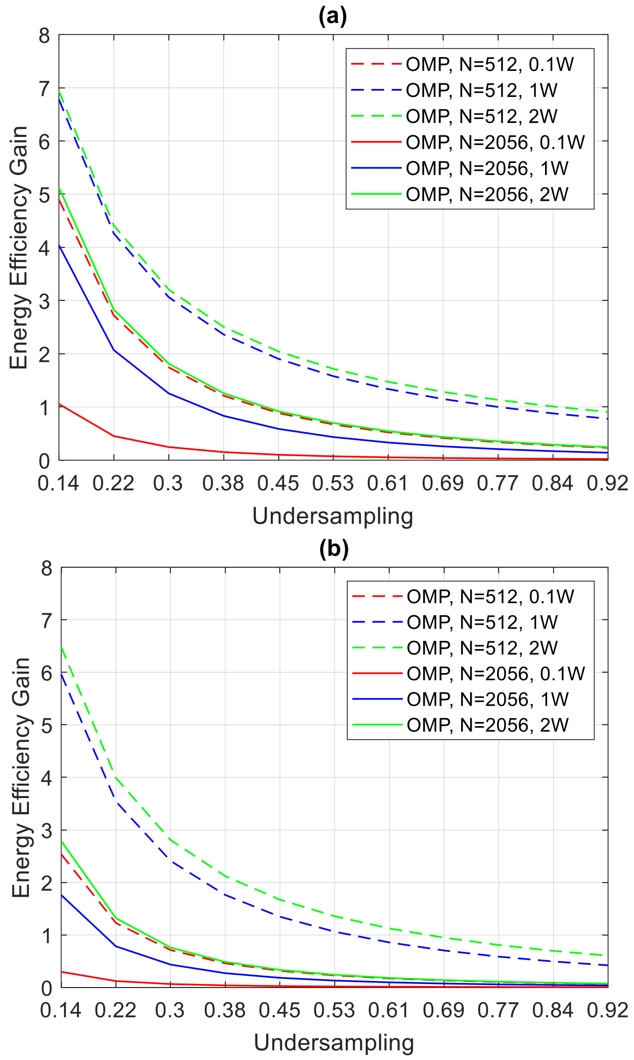

Fig. 4. Energy efficiency gain against the undersampling factor for the OMP algorithm, chirp duration 150 µs and different N and radar power combinations as indicated in the legend. The number of recovered Doppler profiles: (a) – 1, (b) – 4. The number of recovered samples for the OMP algorithm is M/4.

From Fig. 2 and 3 we observe that the energy saving by using BPD is possible but is significantly limited in contrast to OMP. By the most of presented parameters BPD has negative impact on the energy efficiency, since the processing energy prevails over the acquisition energy.

The dashed green and blue lines in Fig. 2 exhibits the energy saving gain by using OMP and almost coincide, since the processing energy is much smaller than the acquisition energy and, hence, the energy saving gain approaches its limit. The limit is equal to N/M under assumption of zero processing cost. The number of recovered samples S in case of using OMP is 4 times less than the number of sent chirps.

V. Classification Test

To solve the classification task mentioned in Section II we use a simple neural network with one hidden layer. The size of the input and hidden layers is equal to 128. The activation function is the rectifier. Dropout rate is 0.5.

The results of classification depend on many parameters, e.g. data preprocessing, optimizer, regularization and so on. The aim of this work is to estimate if the classification of recovered Doppler profiles is possible, whereas the profiles are not artificially sparse, rather real signals. Therefore we present the best results we achieved after tuning some parameters. We suppose that better results are achievable but it is a task for a future work.

Fig. 5 exhibits classification results for two test sets. Namely,

- one with the same fan voltages and orientations as in training set (Fig. 5a), let us call it set 1;

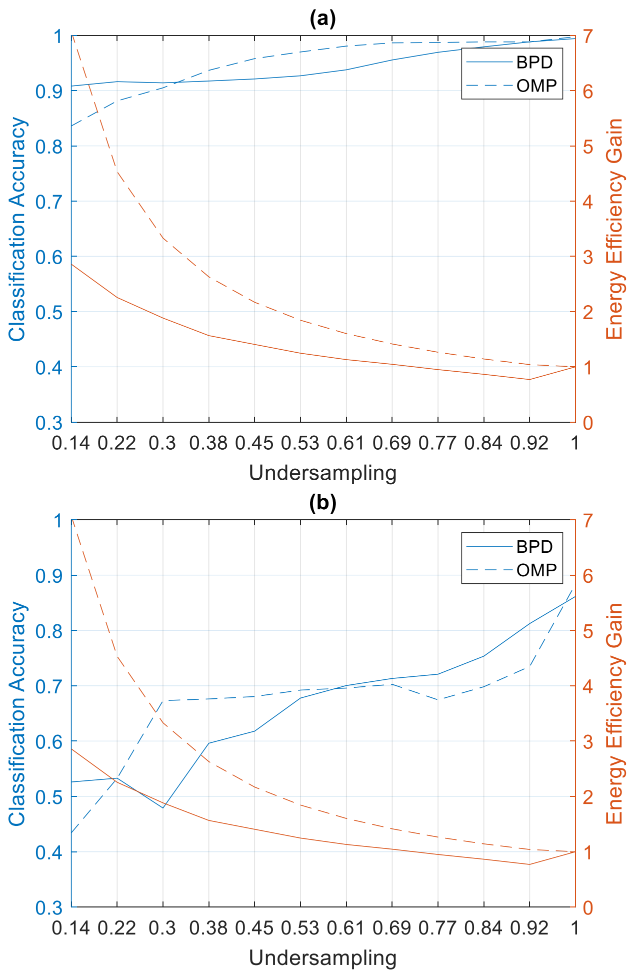

Fig. 5. Classification accuracy and potentially achievable energy efficiency gain against the undersampling factor. Chirp duration is 150 µs. The number of recovered Doppler profiles is 1. (a) – set 1, (b) – set 2. The number of recovered samples for the OMP algorithm is M/3.

- another with the fan voltages and orientations lying between the corresponding values of training set (Fig. 5b), let us call it set 2.

Fig. 5 shows also the energy saving gain for a 1W-radar. The right most values correspond to non-CS approach (undersampling factor equals 1), which as expected provides better classification accuracy. The classification of the reconstructed spectra is more affected by the difference between training set and test set.

Reducing the number of sent chirps one loses on classification performance due to decreased amount of information about weak Doppler parts. For set 2 this effect is more noticeable but the accuracy decreases non-monotonically. From our point of view this shows the existence of improvement room.

VI. Conclusion

In this work we showed that the energy saving through the use of CS in FMCW radars is possible. The claimed effect is achieved by sending less ramps and following recovering of Doppler profiles. By some parameters the amount of energy, which could be saved while RF fronted is sleeping, exceeds the amount of energy required to recover the Doppler profiles.

The profiles recovered under these parameters can be used to solve a classification task. But in this case the neural network is more sensitive to the difference between a training set and a test set.

The presented results can serve as a start point for future work, where it should be cleared which combination of CS algorithm, data preprocessing and neural network parameters provides higher accuracy and allows saving more energy.

Acknowledgment *(Heading 5)*

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