Compressive Sensing and DVB-T-Based Passive Coherent Location

Edison Cristofani[1,2], Osama Mahfoudia[1,3], Mathias Becquaert[1,2], Xavier Neyt[1],
François Horlin[3], Nikos Deligiannis[2,4], Johan Stiens[2,5] and Marijke Vandewal[1]

[1]CISS Department, Royal Military Academy, Brussels, Belgium
[2]ETRO Department, Vrije Universiteit Brussel, Brussels, Belgium
[3]Dept. OPERA,Université Libre de Bruxelles, Brussels, Belgium
[4]SSET-department, Imec, Leuven, Belgium
[5]iMinds, Ghent, Belgium

***Abstract*— For some applications, data burden can become a problem if the system needs to resolve targets accurately. Passive coherent location using digital video broadcast signals is not an exception: large amounts of data need to be acquired, transferred, and stored for processing. Redundancy in signals can be exploited thanks to compressive sensing by means of sparsity in a given domain, random down-sampling the received signal and discarding unnecessary data. However, not all applications are suitable and may not be robust enough. This paper will present preliminary results of passive coherent location and compressive sensing based on signal modelling and Monte-Carlo simulations.**

I. Introduction

TARGET location using transmitters of opportunity has been greatly studied in the recent years. These transmitters can be of diverse nature, including civilian broadcast services offered in regulated frequency bands under the conditions of having access to the originally, direct-path transmitted signal. The ubiquitous presence of terrestrial digital video broadcast (DVB-T) in urban and rural areas and the known position of local broadcast towers make these signals an interesting option for Passive Coherent Location (PCL). The algorithm typically used in PCL is based on the matched filter, known as the Amplitude-Range-Doppler (ARD) [1, 2]. One of the most important downsides of PCL is cumbersome data volumes if target tracking is envisaged.

II. Data Volume Challenges and Compressive Sensing

Improving the PCL system's range resolution is possible by collecting data from several DVB-T channels in parallel [3]. The Doppler frequency resolution, indicating the target's velocity towards or from the receiver, will be in direct accordance with the number of recorded symbols. However, recording several channels is not possible for current affordable software defined radios such as the Ettus B100, which is limited by the USB 2.0 standard [3], allowing a maximum effective transfer rate of around 40 MB/s towards the host. The data rate for one DVB-T channel in 8k mode is about 32 MB/s [4], reducing to just one the number of channels per host computer.

Compressive sensing (CS) is based on recovery of sparse data by applying random sampling [5] which, in principle, can drastically reduce recorded data volumes. Sparsity can be understood as the number of elements that are needed to represent one signal. The fewer elements needed, the sparser the signal is. Typically, modelling the expected scene echoes and creating a dictionary of possible targets is a satisfactory option. This is possible thanks to the perfect knowledge of the DVB-T pilot carriers and their time evolution, as described by the ETSI EN 300 744 standard [4]. The presence of continuous and scattered pilots in the received signals and their cyclic behavior enables creating a representative-enough dictionary, despite the unknown data being transmitted in the data carriers. This implies solving a minimization problem with an over-complete measurement matrix or dictionary. Theoretically, infinite solutions can be found but thanks to the countless developed CS reconstruction algorithms (some examples are the greedy algorithm Orthogonal Matching Pursuit (OMP) and convex relaxation using the l1-norm minimization algorithm [6]), a valid reconstruction can be obtained provided that a balance is found between using a not too low down sampling rate and having a not too complex scene (low sparsity). Due to the enormous size of the generated dictionaries, the l_1-norm algorithm cannot be applied within normal time frames. Therefore, the computationally simpler OMP algorithm is preferred in this text over convex relaxation.

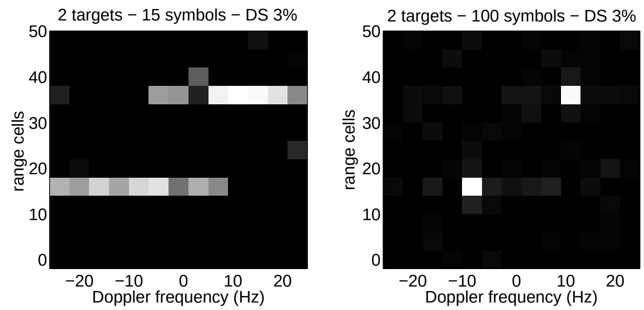

Fig. 1. Two targets are simulated with $DS = 3\%$ and reconstructed using CS. Left, 15 symbols: target smearring in Doppler frequency. Right, 100 symbols: the location of both targets is precise.

III. Simulated and Real Experiments

Initial results are obtained by generating a dictionary describing a scene ranging from 0 to 50 range cells (each cell is 33 m) and a Doppler frequency ranging from $-25\,Hz$ to $+25\,Hz$. For testing purposes, a synthetic signal is generated including two targets at different ranges and velocities described by (-15 cells, -7 Hz) and (-35 cells, $+12\,Hz$). In Figure 1, two CS reconstructions using a down-sampling (DS) rate of 3% on the original data are shown to illustrate the influence of the number of symbols considered in the processing. As expected, the ranges are correctly identified in both cases given the sufficient bandwidth of the single recorded channel. However, using only 15 symbols causes a large uncertainty when extracting the Doppler frequency although an approximation can be inferred. The more symbols

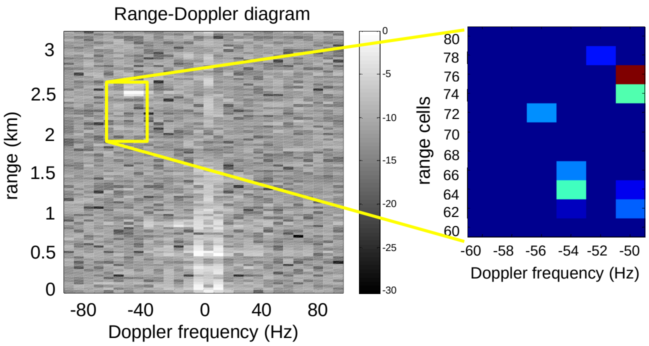

Fig. 2. Results for one target at 2.5 km and $-50\ Hz$. Left, image produced by the ARD algorithm and the full measurement. Right, a reconstructed image using the OMP algorithm and $DS = 3\%$.

are selected, the smaller the uncertainty becomes, reaching a saturation point at around 100 symbols.

Real measurements of a commercial airplane climbing after takeoff were obtained with an 11-dBi Yagi-like antenna used for domestic reception of DVB-T broadcasts (channel 22, 482 MHz). The target was in a direct line-of-sight with the receiver during the whole 10-second recording. As a first attempt and for demonstration purposes, only 100 symbols or 89.6 ms are considered to ensure that the target stays in one single range and Doppler bin. The same synthetic dictionary generated for simulations can be used for reconstructing real scenes, discarding the extremely cost-ineffective and unlikely option of populating it with all possible real acquisitions. In Figure 2-left a reconstruction of the scene is shown using the conventional ARD algorithm, where one target located at 2.5 km and at around $-50\ Hz$ is clearly seen, as well as clutter around 0 Hz and closer ranges, namely buildings nearby the receiver. The graph on the right side shows the CS reconstruction results for a sector of the scene. The brightest point corresponds to the actual position of the target, whereas the remaining points are reconstruction noise due to uncertainty created by the slight but expected mismatch between the received signal and the models.

The robustness of CS applied to PCL is investigated thanks using Monte-Carlo simulations, in which probabilities of detecting the airplane are drawn under different signal-to-noise ratio (SNR) conditions. White noise was added to the already existing measurement noise in the surveillance signal, the total estimated SNR varying from -30 dB to +30 dB (no supplementary noise). A probability of false alarm (P_{fa}) of 10^{-4} is set, with a total of 1,000 trials per SNR value were performed using cell averaging constant false alarm rate detection. For each trial, a different pseudo-sampling sequence was considered for minimizing the effects of randomness in scene reconstruction. In Figure 3, two graphs show P_d values for all SNR values and random DS rates of 0.1%, 0.5%, 1%, 2%, and 5%. The graph in Figure 3-top describes the results for 50 symbols, yielding P_d values close to 1 for DS rates of 1% or above and with $SNR \geq +5\ dB$. Keeping only 0.1% of the original data is noticeably insufficient with $P_d < 0.4$, whereas keeping 0.5% produces P_d rates close to 0.9, opening the way for high reconstruction rates using very low data volumes. This robustness against noise is even clearer in Figure 3-bottom, with perfect reconstruction rates for 100 symbols and

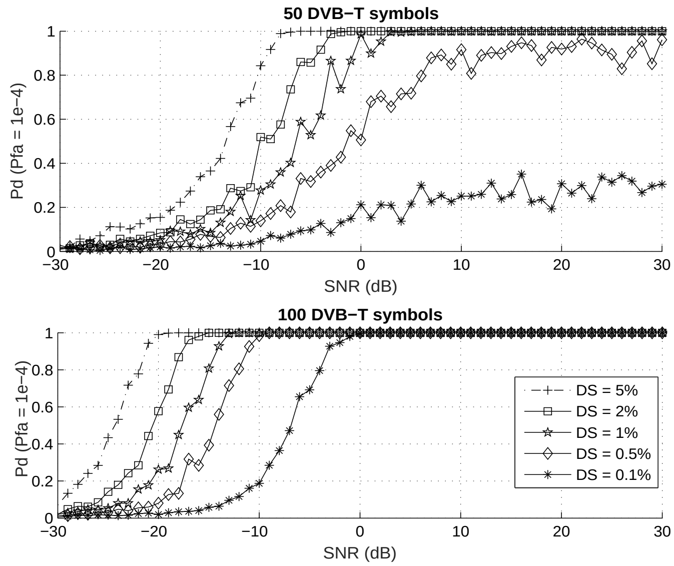

Fig. 3. Probability of detection vs. SNR under different DS rates for: top, 50 DVB-T symbols; bottom, 100 DVB-T symbols.

$DS = 0.1\%$ and $SNR = 0dB$. For the highest DS rate tested, $DS = 5\%$, perfect results are obtained as from $SNR = -20\ dB$.

IV. Results and Future Work

The preliminary work presented in this document show promising results based on both simulations and actual PCL measurements using DVB-T signals as illuminators of opportunity available at all times. Under typical noise and clutter conditions, the target can be perfectly located just using 0.1% of the typical data stream. Randomly down-sampling right from the software radio's buffer allows a considerable data volume reduction, enabling the acquisition of multiple DVB-T channels by one single host, therefore improving the system's range resolution. Longer measurements are also possible, thus increasing the Doppler frequency resolution. Under the assumption that the target follows a smooth trajectory, the reconstructed range and velocity for a given time lapse may be used as a priori knowledge for target tracking. This knowledge is considered as side information, limiting the size of the sectors to be reconstructed and reducing even further the data volume required for high detection rates.

References

[1]. D. Petri et al., "High range resolution multichannel DVB-T passive radar: Aerial target detection," *2011 Tyrrhenian International Workshop on Digital Communications - Enhanced Surveillance of Aircraft and Vehicles*, Capri, 2011, pp. 129-132.

[2]. J. E. Palmer, H. A. Harms, S. J. Searle and L. Davis, "DVB-T Passive Radar Signal Processing," in *IEEE Transactions on Signal Processing*, vol. 61, no. 8, pp. 2116-2126, April15, 2013.

[3]. USRP™ B100 bus series. ETTUS, 09/2012. [Online] Available: .https://www.ettus.com/content/files/kb/application_note_selecting_a_usrp.pdf

[4]. ETSI EN 300 744 V1.6.2 (2015-10) Digital Video Broadcasting (DVB);. Framing structure, channel coding and modulation for digital terrestrial television. ETSI, 01/2017. [Online] Available: http://www.etsi.org

[5]. D. Donoho, "Compressed sensing," IEEE Trans. Inform. Theory, vol. 52, no. 4, pp. 1289-1306, Apr. 2006

[6]. Y. C. Eldar and H. Rauhut, "Average Case Analysis of Multichannel Sparse Recovery Using Convex Relaxation," in IEEE Transactions on Information Theory, vol. 56, no. 1, pp. 505-519, Jan. 2010.