NIMFEIA

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Report on data handling scripts

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1. Handling gesture data for Brownian skyrmion reservoir

As part of the NIMFEIA project, scripts had to be written to feed the gesture-data into a Brownian skyrmion reservoir. This report describes the procedure on which these scripts are based, which are focused on adapting the input dimension to match the number of desired inputs for time-multiplexing. Additional aspects of the actual magnetic reservoir employed as well as the results obtained with it are described in Ref. 1.

The dataset consists of 4800 measurements of 4 classes of gestures: “0: push”, “1: swipe left”, “2: swipe right” and “3: no gesture” and was already successfully used to train spiking neural networks. Varying people stood at the same position in regard to a radar sensor and anonymously performed hand gestures according to the classes. Every gesture measurement consists of 23 frames taken in real-time. The motion was detected by two Infineon Technologies radar sensors of the type BGT60TR13C. The data has to be transformed by exploiting micro-Doppler effects Ref. 50, and obtaining Doppler maps, as described in Ref. 3 and Ref. 4. Mainly, Fourier-transformations are performed to obtain the Doppler frequency shifts, resulting in two-channel maps (Range-Doppler and Range-Angle), showing the angle or the amplitude against the relative velocity and the distance to the radars. Figure 1 shows one exemplary “0 –push” gesture after the Range-Doppler (RD) and the Range-Angle (RA) transformation. As we want to minimize the data fed into the reservoir, we restrict ourselves to only one voxel of the maps. To find the one containing the most information, we perform multi-class radial basis functions Support Vector Machine (rbfSVM) classification (see Refs 5,6) on every possible index (Range-Doppler/Range-Angle), to find the input voxel (23 consecutive time-steps of one particular index) that performs best on all 4 gestures at once. We further checked if data pooling (Average of 1x1, 2x2, or 4x4 tiling) increases classification. Every input was trained with K-Folding and $K = 10$ to obtain statistically robust values. The best score was obtained by averaging the performance of the K test sets. The respective voxel is marked with a red box in Figure 1. Reducing the data to one input is also required to obtain experimental data in a reasonable time, as the manual experiments are time-consuming and must be taken with care. In a non-proof-of-concept device, this training process could of course be automatized using specifically tailored hardware. The pairwise results shown in the main text of Ref. 1 are obtained by the same voxel, namely the one that performed best.

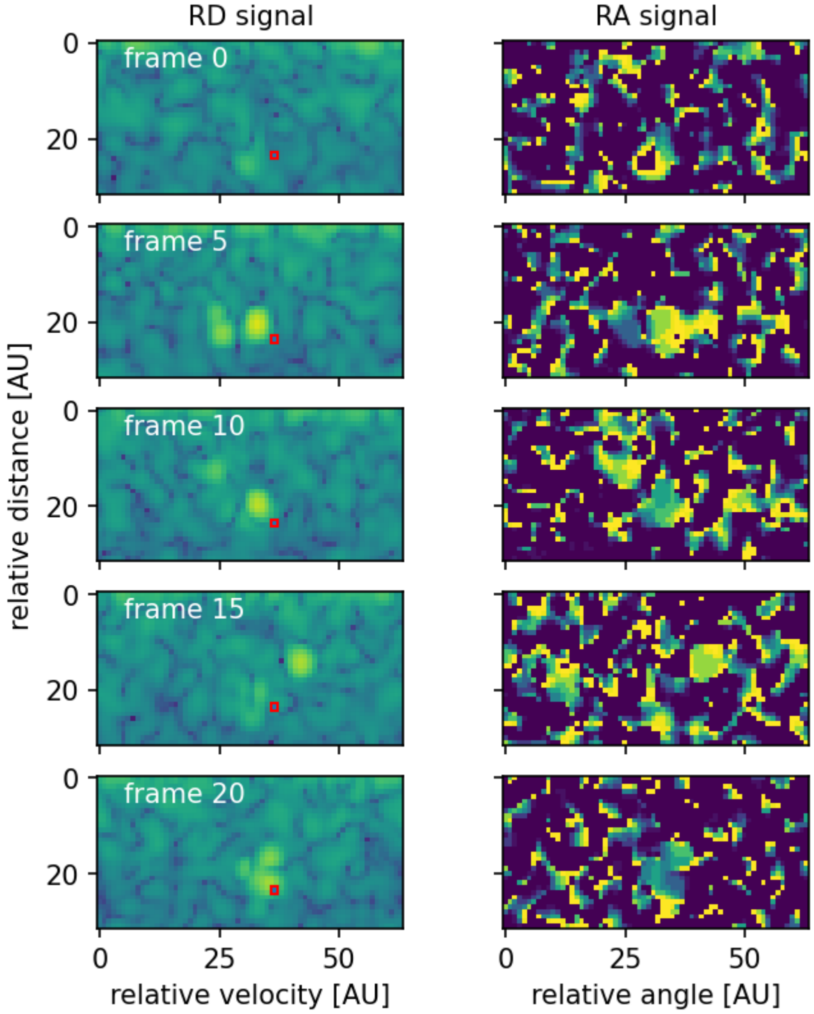

Figure 1: *Range-Doppler and Range-Angle maps for one specific gesture and one-time frame. Apart from noise, one can detect two blobs in the maps, one referring to the person's body gesticulating, and the other to the hand doing the movement. We also marked the voxel with a red box that was used as input for our Skyrmion Reservoir.*

References

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