Supplementary Materials

A: VALIDITY OF METHOD AFTER HAGERMAN & OLOFSSON

We checked whether the assumption of short-term linearity was valid for the algorithms, as it is a necessary criterion for a reliable outcome of Hagerman & Olofsson's method. For this we used Olofsson & Hansen's method (2006), in which the nonlinear distortion of a system is measured using the fact that the real and imaginary parts of the analytical signal corresponding to the input signal to a system after being passed through a nonlinear system are no longer a Hilbert pair. The nonlinear distortion depends mainly on the algorithm, but can also be influenced by the processed signal, for example by its frequency content. Therefore, the analysis was done using the acoustic environments from experiment 2, to have a range of different input signals. The level of the estimated nonlinear distortion relative to the level of the processed superposition of target and noise signals is listed in Table S1 for all algorithms and in all acoustic environments of experiment 2. If the algorithm is short-time linear, the level of the estimated distortion should be very low compared to the level of the processed superposition of target and noise signals. Acceptable levels for the nonlinear distortion are values below -20 dB, because then the influence of the nonlinear distortion on the SNR is low. It can be seen in Table S1 that this was the case for all algorithms except AMVDRb. For the AMVDRb, the setting with the fastest adaptation time showed high levels of the estimated nonlinear distortion. This could also be heard when listening to the output signals. For the intermediate setting the level of the estimated distortion was still above threshold and some distortion could still be heard in the output signals. The slowest setting had a low estimated distortion level and there was barely any distortion audible in the output signals. This means that the assumption of short-time linearity is not valid for the fast and intermediate settings. Therefore, the signals obtained using the method after Hagerman & Olofsson and the SNR calculated from these signals might be inaccurate for these settings. To explore the nature of the distortions, spectrograms were plotted in supplementary materials B.

Table S1: Level of the estimated nonlinear distortion of the method after Hagerman & Olofsson relative to the level of the processed target plus noise signal in dB for each algorithm and environment.

Algorithm \ Environment		cafeteria dualtask	cafeteria listeningonly	lecture-hall	living-room	street active	train station
D&Sb		-55.9 dB	-54.2 dB	-57.2 dB	-56.4 dB	-59.3 dB	-51.6 dB
ADMb		-52.9 dB	-51.3 dB	-56.8 dB	-58.3 dB	-57.4 dB	-59.0 dB
SBb		-43.9 dB	-43.6 dB	-40.0 dB	-46.2 dB	-40.0 dB	-40.6 dB
AMVDRb	**fast**	**-7.4 dB**	**-8.9 dB**	**-0.3 dB**	**-6.9 dB**	**-7.3 dB**	**-3.3 dB**
	inter-mediate	**-18.8 dB**	**-18.6 dB**	**-14.7 dB**	**-18.5 dB**	**-18.5 dB**	**-13.2 dB**
	slow	-28.5 dB	-29.7 dB	-25.2 dB	-31.0 dB	-29.0 dB	-26.6 dB
BNR		-45.6 dB	-44.8 dB	-45.1 dB	-45.1 dB	-46.6 dB	-46.9 dB
SCNR		-22.1 dB	-20.5 dB	-30.2 dB	-31.6 dB	-26.8 dB	-26.4 dB

B: SPECTROGRAMS OF ESTIMATED NONLINEAR DISTORTION

To explore the nature of the nonlinear distortions in the AMVDRb algorithm output, spectrograms were plotted of the nonlinear distortions estimated with the method after Olofsson & Hansen (2006) for the recorded signals of the *cafeteria*$_{listeningonly}$ environment without head movement in Figure S1. The plots confirm that the estimated nonlinear distortion of the fastest setting has the highest power. The power of the distortions is mainly in the low frequency range below 1 kHz.

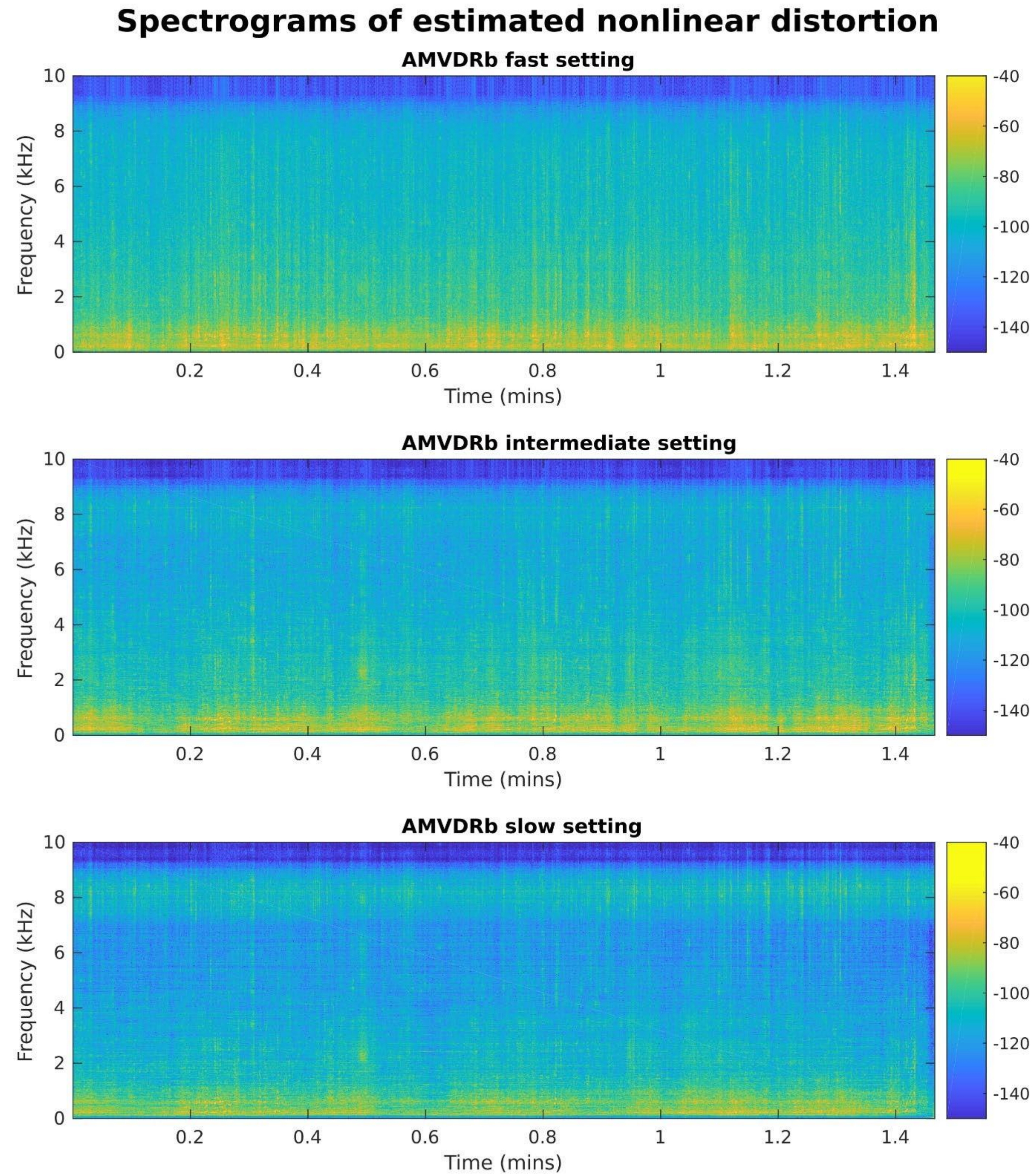

Figure S1: Spectrograms of estimated nonlinear distortion for the AMVDRb algorithm with the three different settings, using the method after Olofsson & Hansen (2006). The estimated nonlinear distortion in the *cafeteria*$_{listeningonly}$ environment without head movement is plotted. The colorbar shows the power in dB.

C: POLAR PLOTS OF SNR BENEFIT, TARGET GAIN AND NOISE GAIN

Polar plots were made of the SNR benefit, target gain and noise gain of the left hearing aid output for the algorithms in all three scenarios of experiment 1, in order to characterize them. Signals were recorded by turning the simulated listener in the respective directions and then recording for 10 seconds: the first 5 s for adaptation and the second 5 s for the calculation of the SNR and gain. The polar plots of SNR benefit, target gain and noise gain of the algorithms in the three different scenarios are displayed in Figure S2. It can be seen that benefit and gain of the BNR and SCNR algorithms did not depend on the direction, these algorithms are omnidirectional. All the other algorithms are beamformers and directional. The D&Sb and ADMb algorithms had a cardioid target gain pattern, whereas the patterns of the SBb and AMVDRb algorithms were narrower towards the target direction. Comparing the average target gain for the different scenarios showed how much the algorithms adapt to the noise scenario. For the D&Sb and SBb algorithms, the average target gain polar pattern was exactly the same in all scenarios, because these algorithms were non-adaptive. The ADMb algorithm adapted only minimally, but the other algorithms adapted more. Furthermore, the SNR benefit patterns indicate the direction of optimal benefit for each directional algorithm in each scenario. In scenario 1, with one noise source at +120°, the direction of optimal benefit for the ADMb was about -30° and for the D&Sb about -80°. In the other scenarios and for the other directional algorithms, the direction of optimal benefit was uniformly towards the target source.

D: INPUT AND OUTPUT SNR EXPERIMENT 2

The mean input SNR and output SNR over time for all algorithms in all environments are plotted in Figure S3. The plot shows that the different head movement traces also result in a different output SNR, which means that the algorithms did not just compensate for the differences in input SNR due to head movement, but that their performance is really affected by the head movement. The plot also shows that the range in output SNR is in some cases larger than the range in input SNR. This means that there are other factors than the input SNR affecting the output SNR.

E: ALGORITHM BENEFIT PER ROTATIONAL HEAD SPEED

Scatter plots of the algorithm benefit versus the horizontal angular rotational head speed, including regression lines, are shown in Figure S4. The plots show that the algorithm benefit is constant over the head speed for all algorithms (slopes and regression values close to zero), so there is no dependency and maladaptation is not contributing to the movement effect.

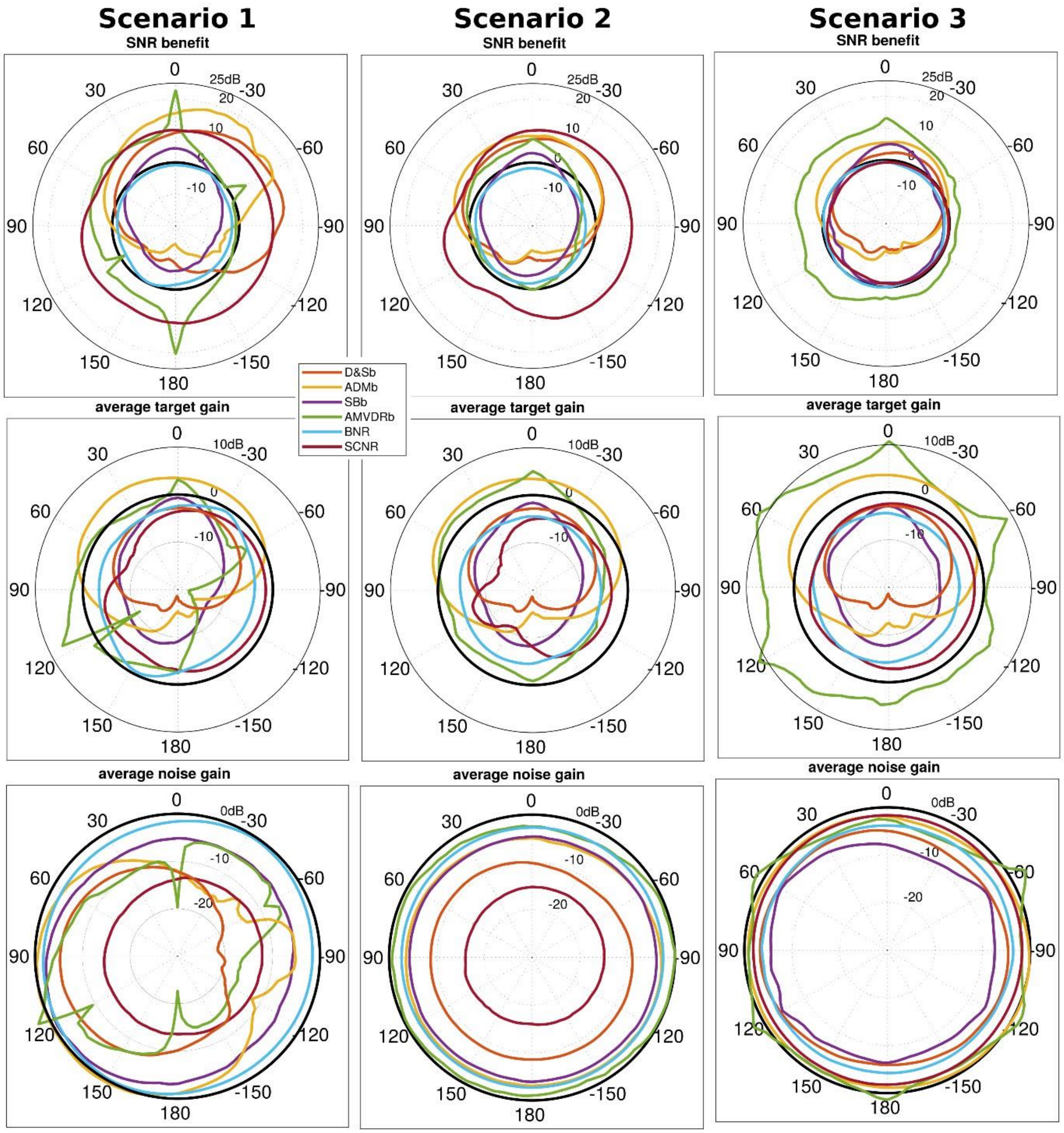

Figure S2: The directional SNR benefit, average target gain and average noise gain of the algorithms in scenario 1 (left column), scenario 2 (middle column) and scenario 3 (right column) from experiment 1 at -5 dB long-term input SNR for the left hearing aid output. Signals were recorded by turning the simulated listener in the respective directions and then recording for 10 seconds, the first 5 s for adaptation and the second 5 s for the calculation of the SNR and gain.

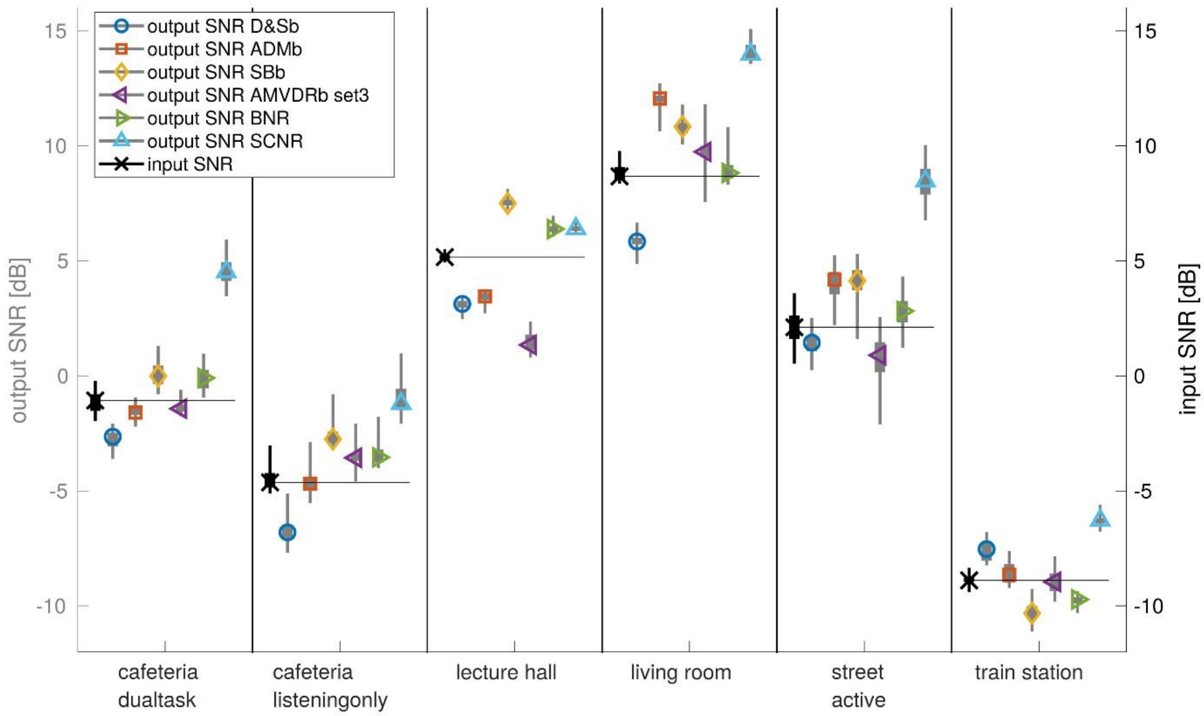

Figure S3: Mean input and output SNR over time for all algorithms, movement traces and environments. Box plots show the median (different symbol and color for each algorithm), 25th and 75th percentiles (thick line) and the range (thin line). The range in input SNR and output SNR shows that different head movement traces result in a different input SNR and output SNR.

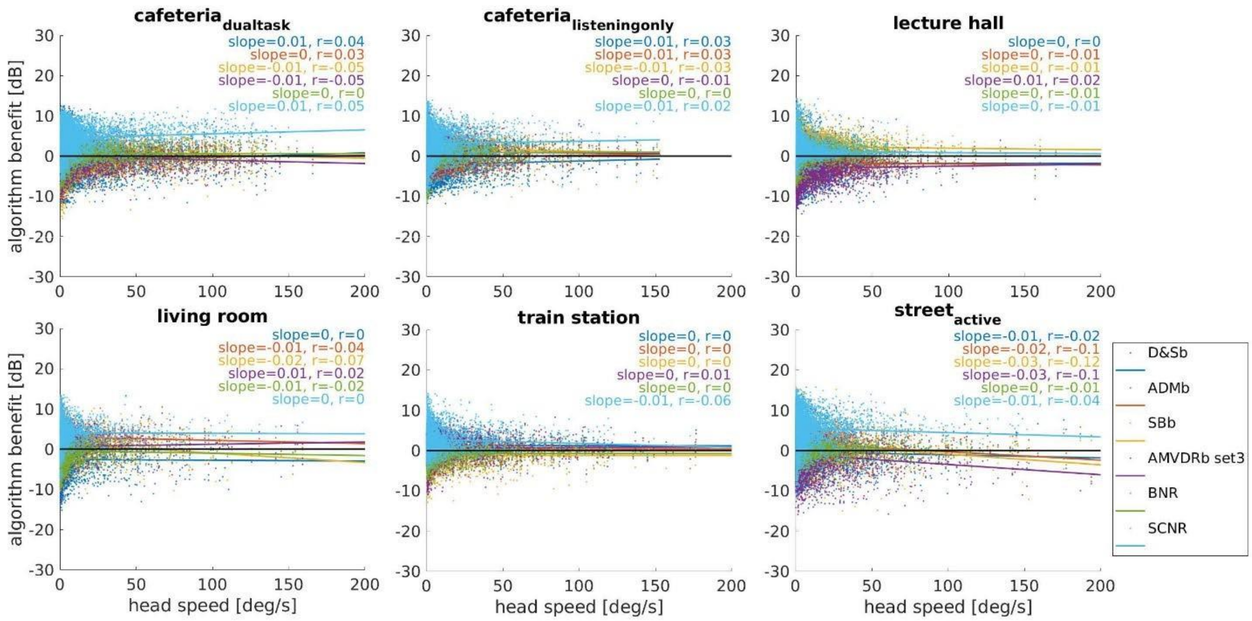

Figure S4: Algorithm benefit as a function of horizontal rotational angular head speed for all algorithms in all environments. Linear regression lines were plotted through each set of data points. The regression values and slopes of the regression lines are displayed in the top right corner with matching colors. This shows that the algorithm benefit is not dependent on the head speed.