

Millimeter-Wave SAR-Imaging With Radar Networks Based on Radar Self-Localization

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Abstract—In this article, an imaging system is presented, which is solely based on distributed radar sensors mounted on a mobile platform, such as a robot or vehicle. The data of multiple distributed sensors, which perform fast chirp-sequence measurements, are processed together. This enables both a highly accurate ego-motion estimation and a coherent synthetic aperture radar (SAR) imaging based on it. This system is independent of any additional sensors, such as an inertial measurement unit (IMU) for motion estimation or a global navigation satellite system (GNSS) for self-localization. Measurements using four sensors are carried out at 77 GHz to verify simulations.

Index Terms—Ego-motion, motion estimation, networks, radar systems, radar transceivers, sensor, synthetic aperture radar (SAR).

I. INTRODUCTION

SYNTHETIC aperture radar (SAR) enables high-resolution imaging based on radar sensors with simple hardware. This is achieved by the use of multiple measurements that are captured during the sensors' movement along a precisely known trajectory. The SAR principle is widely used for airborne and spaceborne applications, such as imaging and observation of the earth's surface [1]. These radar systems need to bridge large distances and usually operate at wavelengths up to the X-band [2] whereby typically resolutions in the meter range are reached. The achievable image resolution of an SAR system depends on the range resolution and on the length of the synthetic aperture [3]. In addition, the precise knowledge of the trajectory is a key factor for the image reconstruction out of multiple acquisitions [4].

In contrast to spaceborne SAR, this article presents a short-range SAR system based on the motion of a ground vehicle, such as a car or robot. In the field of automotive and industrial applications, the radar sensors often operate in the 77-GHz band at bandwidths up to 1 or 4 GHz [5]. The achievable range resolutions promise excellent image resolutions, but in turn the short wavelength of 3.9 mm places high demands on the precision of the estimated trajectory [6]. Hence, the technique for motion estimation becomes crucial to the overall image quality and accuracy [7]. Ground-based SAR

often employs inertial measurement units (IMUs) [8], wheel sensors [9], and global navigation satellite systems (GNSSs) in order to estimate the trajectory of the mobile platform [10]. While high-grade IMUs provide low drift errors at high cost, typical systems underlay a certain drift in the derived trajectory [11], [12]. The approach proposed in this article directly extracts the trajectory from the same radar data that are used to generate the high-resolution image. Thus, the approach works independently of additional sensors by using an absolute localization toward the targets in the scene.

This radar-based motion estimation benefits from an increasing number of radar sensors that are mounted on mobile platforms. They cover a larger field of view (FoV) providing information about the environment to higher level systems. While individual processing of the sensors' data is conceivable, a joint evaluation of multiple sensors offers additional opportunities for sensors with overlapping FoVs. Large spatial distances between the sensors enable different perspectives on a commonly observed target. Thus, targets can be detected more robustly. In addition, for a nonstationary scene, the relative velocities that are observed from different sensor locations vary for a common target. This provides the necessary information for an estimation of the ego-vehicles motion vector within a single measurement snapshot.

Utilizing the estimated trajectory of the mobile platform together with the spatially distributed sensors allows for innovative joint imaging using low-cost radar sensors. The approach of processing of multiple sensors jointly requires just a motion of a few centimeters to yield high resolution.

II. CONCEPT AND SYSTEM ARCHITECTURE

The system concept comprises several sensors that are distributed around a mobile platform, as it is exemplarily shown in Fig. 1. The sensors are distributed in such a way that not only overlapping FoVs are achieved, but also the spread on the mobile platform is as large as possible. The single-sensor antenna pattern preferably has a wide FoV in the azimuth plane in order to allow for large distances between the sensors with overlapping FoVs. A wide distribution is beneficial for a good ego-motion estimation, and at the same time, it allows for a multiperspective SAR-imaging of the scene in front of the sensors.

The overall system concept requires just one receive and one transmit channel per sensor. Furthermore, the sensor network operates incoherently, whereby the measurements are synchronized in time by a trigger signal to prevent mutual interference

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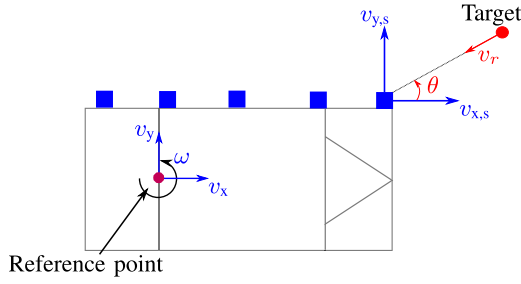


Fig. 1. Exemplary distribution of sensors around a mobile platform [13]. The sensors experience different range and velocity observations of a joint target due to their spatial distribution.

within the network. This results in a simple and cost-effective system for the radar imaging with multiple sensors.

To allow for both simultaneous motion estimation and imaging, all radar sensors transmit sequences of fast frequency-modulated continuous-wave (FMCW) ramps, also known as chirp-sequence modulation [14], [15]. A chirp sequence consists of a multitude of K FMCW ramps each having the RF bandwidth f_B and the duration T_c . The ramps are repeated in a fixed interval T_{RRI} , which is composed of the ramp duration T_c , a down-ramp to reset the signal to the start frequency, and a break time.

The chirp repetition interval T_{RRI} is a crucial factor for the complete imaging system. It determines the absolute unambiguous range for the velocity measurement and the unambiguousness of the synthetic antenna array at the same time. In view of the SAR processing, the spatial sampling distance should not exceed $\lambda/2$ to avoid grating lobes, which would occur as ambiguities in the image. On the other hand, the unambiguous determination of the Doppler frequency and, thus, the speed of motion also depends on the ramp repetition rate. The relationship between the spatial sampling and the transmitted chirp sequence is shown in Fig. 2.

Due to a direct-conversion receiver architecture, only small IF bandwidths of the signal need to be considered for analog-to-digital conversion [16]. The operation frequencies of the single sensors in the network are shifted against each other so that the spacing is larger than the IF bandwidth, and thus, interference between sensors that observe a common FoV [17] is avoided. Hence, independent monostatic chirp-sequence measurements can be conducted by all sensors at the same time and are therefore available for a common evaluation. The sensors are distributed on a vehicle with preferably large spacings, but they still need to have overlapping FoVs. This allows for the use of multilateration techniques for target localization with single-channel radar sensors. Alternatively, multichannel sensors can perform classical angle-of-arrival (AoA) estimation. Furthermore, the multiperspective view of the sensors on the environment is beneficial for an accurate estimation of the actual motion of the vehicle. Here, the variety of targets that are observed at different angles with respect to each sensor and their radial velocities allows for a precise motion estimation within a single chirp-sequence measurement [13]. In addition, each sensor on the mobile platform is able to create a synthetic aperture during motion, which is denoted as subaperture. These subapertures are captured

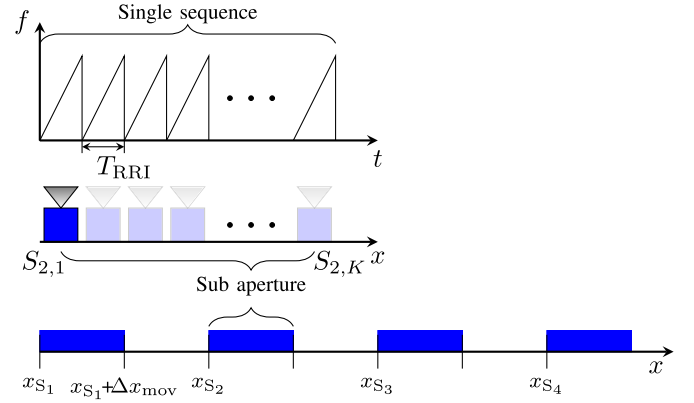


Fig. 2. Relationship between spatial movement of the sensors (blue squares) and transmission of K FMCW ramps at an interval T_{RRI} , denoted by the index k in $S_{n,k}$. Exemplary depiction of the subapertures of four sensors (S_1 – S_4) that are mounted on a common mobile platform, resulting in a single sequence aperture. During a sequence, the platform covers the distance Δx_{mov} .

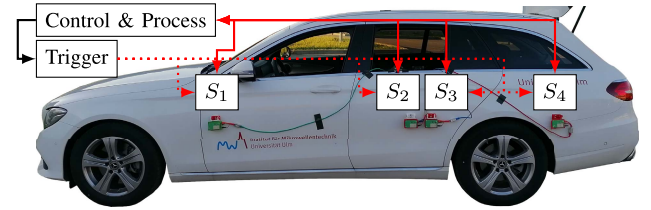


Fig. 3. Experimental system setup with four sensors on a mobile platform. Data processing and control is handled by a central unit. Measurements are triggered simultaneously.

simultaneously as all sensors perform their chirp-sequence measurements at once. The subapertures can be processed individually or contribute to a combined aperture as it is depicted exemplarily in Fig. 2 for four sensors. The measurement setup that is used for the further evaluation of the proposed method is shown in Fig. 3. Four sensors are connected to a joint control and processing unit over Ethernet. This central unit configures the sensors prior to measurement and receives the raw data stream from the sensors. A trigger signal is distributed to the sensors in order to initiate a single sequence measurement.

III. PROCESSING CHAIN

An overview of the total signal processing chain is given in Fig. 4. The first steps are conducted for each sensor individually. The processing is based on the time-domain samples of simultaneously triggered measurements of the sensors. After zero padding, the range and Doppler information is calculated by two consecutive fast Fourier transformations (FFTs) for each sensor. The subsequent constant false-alarm rate (CFAR) peak detection serves as the basis for the target localization and the following ego-motion estimation. At this point, the measurements of all N sensors are combined, resulting in one joint target list and one joint ego-motion estimation for each transmitted chirp sequence.

The final goal, the SAR processing, is achieved by applying various processing steps, which depends on the desired aperture length of the resulting radar image, as shown in Fig. 4. Based on the accurate ego-motion estimation, a precise posi-

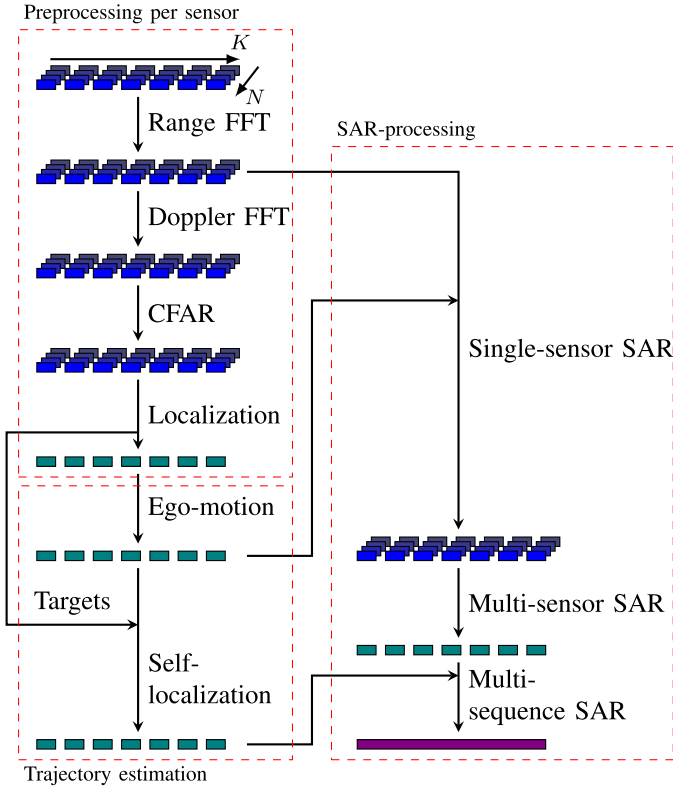


Fig. 4. Overview of the processing steps. The different colors distinguish the different levels of the processing for N sensors and K chirp sequences. Blue data parts (■) are independently processed for all sensors and all measurements. Green parts (■) compose the information of all N sensors and purple (■) denote the combination of all sensor data over multiple chirp sequences.

tion estimation for each transmitted FMCW ramp of each sensor is ensured, whereby an independent SAR processing per sensor is possible while a single sequence is transmitted. A coherent addition of the pixel grids of all N sensors leads to the multisensor SAR image, enabling for a more precise depiction of the environment. For long trajectories with respect to the wavelength, an estimation of the vehicles' drive path using the ego-motion leads to deviations due to time gaps between the measurements. Hence, the movements during a single sequence are considered as subsets of a long trajectory. These subsets are merged to the full trajectory in a global grid by further self-localization based on targets in the scene. Therefore, points of reference are determined from self-localized targets and are associated throughout consecutive measurements. The locations of these points of reference and the estimated ego-motion of each single sequence measurement are used to reconstruct the precise trajectory of the full motion. The joint processing of measurements of multiple sensors in combination with this trajectory reconstruction allows for the generation of a high-resolution SAR image for comparably long arbitrary trajectories.

IV. SINGLE SEQUENCE

A. Target Localization and Ego-Motion Estimation

Prior to the SAR processing, it is necessary to estimate the actual trajectory, which is achieved from the chirp-sequence

measurements of multiple sensors on the mobile platform. The used ego-motion estimation works with three degrees of freedom (DOFs), which are the forward velocity V_x , the side slip V_y , and the yaw rate ω [13]. The 3-DOF motion is estimated for a reference point P_R on the mobile platform. The velocity at each sensor position can be calculated as a function of the geometrical relation between the sensor location and the reference point P_R . The individual sensor movements are important for the following SAR processing.

The ego-motion estimation depends on the angles (θ) as well as the measured relative velocities between the sensors and the targets. The relationship between these velocities, angles with respect to the sensor positions, and the actual 3-DOF movement of the mobile platform can be written as

$$\begin{bmatrix} -V_{n,1}^r \\ -V_{n,2}^r \\ \vdots \\ -V_{n,M}^r \end{bmatrix} = \begin{bmatrix} \cos(\theta_{n,1}) & \sin(\theta_{n,1}) \\ \cos(\theta_{n,2}) & \sin(\theta_{n,2}) \\ \vdots & \vdots \\ \cos(\theta_{n,M}) & \sin(\theta_{n,M}) \end{bmatrix} \cdot \underbrace{\begin{bmatrix} -y_n^s & 1 & 0 \\ x_n^s & 0 & 1 \end{bmatrix}}_{S_n} \cdot \begin{bmatrix} \omega_B \\ V_{B,x} \\ V_{B,y} \end{bmatrix} \quad (1)$$

considering the n th sensor and M targets. The matrix V_n^r consists of all measured relative velocities between a specific sensor n and M targets that correspond to the velocity of the mobile platform. As soon as $M \neq 1$ targets are captured by the N distributed sensors, the equation enlarges to

$$\underbrace{\begin{bmatrix} V_1^r \\ V_2^r \\ \vdots \\ V_N^r \end{bmatrix}}_{V^r} = \begin{bmatrix} D_1 \cdot S_1 \\ D_2 \cdot S_2 \\ \vdots \\ D_N \cdot S_N \end{bmatrix} \cdot \underbrace{\begin{bmatrix} \omega_B \\ V_{B,x} \\ V_{B,y} \end{bmatrix}}_{V_p} \quad (2)$$

This overdetermined linear system of equations can be solved, for example, by a least-squares (LSQ) or an orthogonal distance regression (ODR) approach. Due to an asymmetrical variance of the angle-velocity profile, an ODR-approach yields more accurate results [18].

B. Imaging

In the following, the construction of an image based on a single chirp-sequence measurement of one or multiple sensors is described. As soon as the sensors are moving, the continuous transmission of FMCW ramps is equivalent to a spatial sampling along the motion path as it is shown in Fig. 2. As a result of the estimated ego-motion and the chirp repetition rate f_r , a spatial distance between the sampling points is calculated. To avoid ambiguities, the Nyquist criterion [19] has to be satisfied. Therefore, the chirp repetition time has to be short enough to ensure a distance smaller than $\lambda/2$ between the adjacent spatial sampling points. Based on the estimated ego-motion, the local position of each sensor for any transmitted FMCW ramp can be determined with respect to the first spatial sampling point.

With regard to arbitrary sensor positions, arbitrary motion trajectories, and velocities, equidistant sampling cannot be

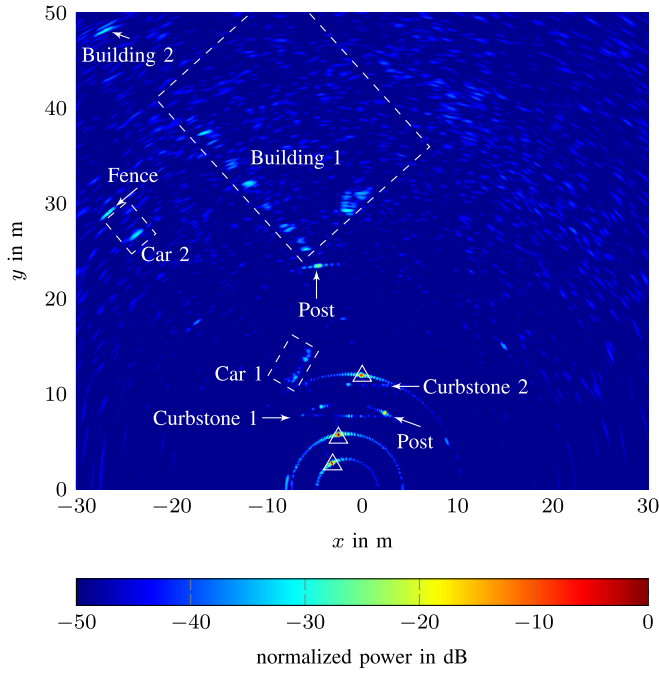


Fig. 5. Image comprising the data of one sensor that moves 7.87 cm. The sensor operates at 77 GHz using a bandwidth of 1 GHz.

ensured. Hence, a backprojection algorithm is used for executing the SAR processing [20]. Due to a linear antenna configuration and a sensor movement within the xy plane, the focal plane is set. First, a grid as the basis for the focused image needs to be defined. The distance r between the K sampled sensor positions for each transmitted ramp k and each pixel is calculated. The associated complex values of the range measurements $A_{r,n,k}$ are coherently projected to each grid cell resulting in

$$G(x, y) = \sum_{k=1}^K \sum_{n=1}^N A_{r,n,k} \exp\left(-j2\pi \frac{f_c}{c}(r - \Delta r)\right) \quad (3)$$

where Δr is the resolution of the range-FFT, f_c is the radars start frequency, and c refers to the speed of light. The backprojection can be performed for data of a single sensor and multiple sensors, which is discussed in the following.

1) *Single Sensor*: The proposed algorithm is applied to one single chirp-sequence measurement of one sensor in the previously described scenario. A small pixel size of 10 mm is chosen to enable a lossless imaging of the scenario. The processed SAR image of one sensor after applying the backprojection algorithm is shown in Fig. 5.

The length of the synthetic subaperture is approximately 7.87 cm resulting from $K = 128$ FMCW ramps per single sequence and a ramp repetition time of $T_{\text{RRI}} = 420 \mu\text{s}$. The sensor operates in the 77-GHz band using a bandwidth of 1 GHz, while the mobile platform moves at a speed of 1.4 m/s.

The imaged scene comprises corner reflector targets and different extended targets, and it is shown in Fig. 6. The results already show an excellent representation of three out of the four corner reflectors and of one parking car (Car 1), as shown in Fig. 5. Further reflections can be assigned to

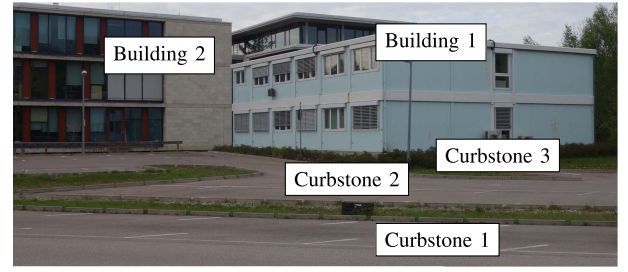


Fig. 6. Photograph of the measurement scene without the two cars and the corner reflectors.

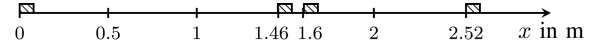


Fig. 7. Representation of the spatial sampling areas or synthetic subapertures, respectively, (■) for the used $N = 4$ sensors and a single sequence.

another car (Car 2) and a wooden fence. Due to the short synthetic aperture for the single sequence and as no windowing is applied on the data over the spatial sampling points, the response of the synthetic aperture corresponds to a sinc function after backprojection. The resulting sidelobes can be clearly seen around strong targets such as the corner reflectors but also weakened around the more distant post. The smaller number of visible sidelobes is due to the lower power of the post. This focused representation of targets and the sidelobes confirm the sufficiently good quality of the prior estimated ego-motion.

In addition, the corner reflectors ($\blacktriangle$), the two buildings (Buildings 1 and 2), curbstones (1 and 2) in front of the car, and light posts can be identified. Noteworthy, the parts of the curbstones are visible, which are perpendicular to the incident wave. Thus, visible parts are limited to the length of the synthetic aperture.

Moreover, the clutter can be clearly seen, resulting in a poor dynamic range between the targets and the clutter level in comparison to the following SAR images. This problem can be partially solved by using multiple sensors, which observe a common FoV.

2) *Multiple Sensors*: The overall concept of the proposed system uses multiple radar sensors with a large spatial distribution for the ego-motion estimation in 3-DOF. Hence, the motion trajectories of each sensor can be calculated with respect to the local coordinate system, allowing a joint SAR processing of all sensors with a common FoV, as shown in Fig. 8.

In the following, the measurements of four sensors observing an exemplary scene are considered. The sensors are installed on the same moving platform with spacings, as shown in Fig. 7. Hence, the velocity of all sensors can be calculated by using the already estimated mobile platform velocity. If the position of all four sensors is known with an accuracy better than $\pm(\lambda/4)$ [21], a constructive addition of the corrected $A_{r,n,m}$ signals is guaranteed. Fig. 8 shows the resulting coherent backprojection of all sensor measurements for a single sequence.

The most striking difference compared with Fig. 5 is the reduced clutter in the background of the image. A reason

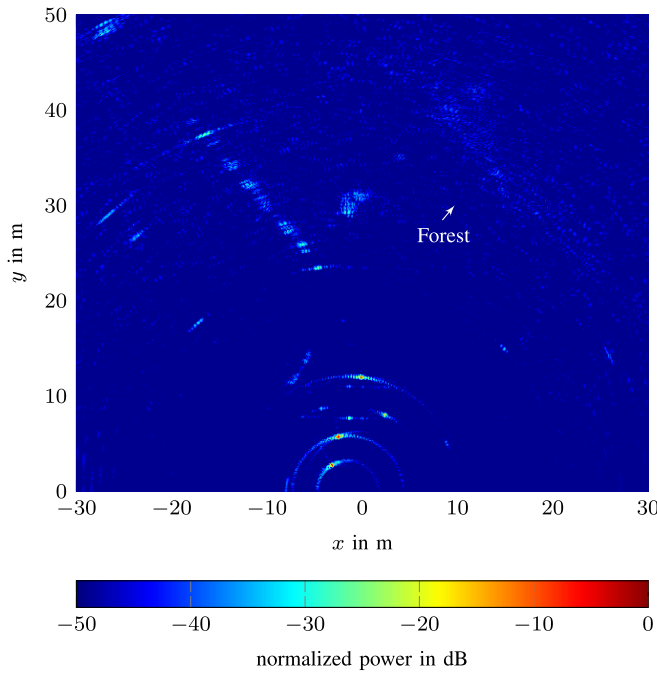


Fig. 8. Image comprising the data of all four sensors at 77 GHz. The sensors are mounted on the same mobile platform with spacings, as shown in Fig. 7.

for the clutter of the single-sensor measurement is the small synthetic aperture. This could be extended from 7.87 to approximately 260 cm by using all four sensors as it is shown in Fig. 7, though the mobile platform has moved the same distance of 7.87 cm.

As shown in Fig. 7, the networks synthetic aperture does not satisfy the Nyquist criterion at a length of 260 cm. Nevertheless, there are no ambiguities as the Nyquist criterion is met within the subapertures of each sensor.

In addition, the contour of the edge of the forest is clearly visible, whereas the shape of the curbstones is only slightly better visible. A zoomed-in view of the car (Car 1) nearby and the distant building are shown in Fig. 9 for the single-sensor and multisensor SAR processing. Here, a clear improvement can be observed in case of a combination of multiple sensors during a single chirp-sequence measurement. The fourth corner reflector is still not visible due to the limited FoVs of the sensors. Moreover, the curbstone is not visible over its entire length. This can be overcome by driving a longer trajectory, whereby the reconstruction of the trajectory requires further effort.

V. MULTIPLE SEQUENCES

As soon as the trajectory becomes longer, it is possible to enhance the SAR image by utilizing the longer synthetic aperture. This is ideally done with continuous radar measurements along the trajectory. In order to be independent of such a strict spatial sampling, it is important to consider interruptions in the measurements' flow. For instance, this can be a pause between two consecutive chirp sequences or a short-term loss of measurement data. The duration of a pause between two consecutive single sequence measurements could, e.g., depend on the maximum possible data rates and thus on the hardware structure of the overall system. However,

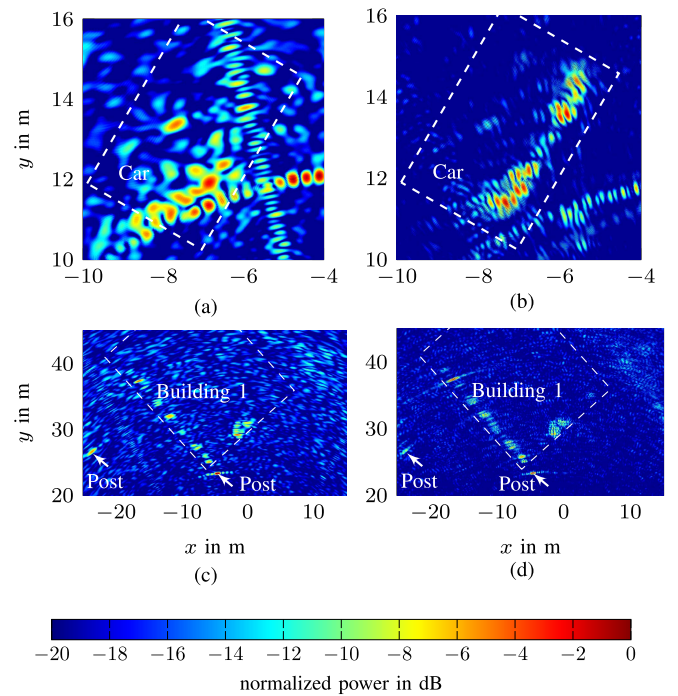


Fig. 9. Comparison of the SAR images of two target objects based on the measurements of a single sensor and multiple sensors. (a) Car 1, one sensor. (b) Car 1, four sensors. (c) Building 1, one sensor. (d) Building 1, four sensors.

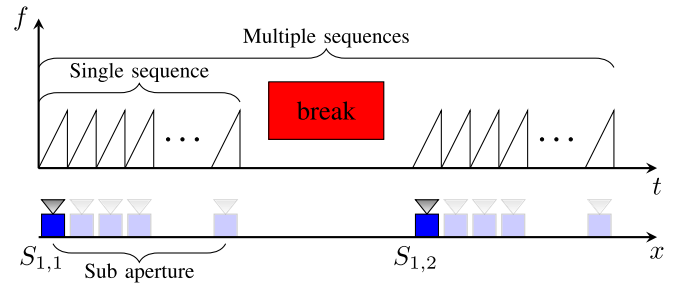


Fig. 10. Position estimation based on dead reckoning for a single sequence (■) and on the basis of stationary targets for multi-sequence localization (■) illustrated by an example with one sensor (first index) at two different positions for different times (second index).

the movement during a pause is not tracked by radar measurements. Hence, the position of the sensors after a measurement can only be estimated by either dead reckoning based on the previously estimated velocities or by a new self-localization based on stationary targets. Dead reckoning assumes a constant movement and suffers from error propagation over time [22]. In contrast, stationary targets can be associated with multiple chirp-sequence measurements, which allows for a radar-based self-localization.

Due to an arbitrary combination of linear and nonlinear movements of the radar sensors, no constant movement during the break between two measurements can be assumed. Therefore, the self-localization allows estimating the position of the radar sensor at the time of transmitting the first FMCW ramp of each chirp sequence with regard to a global coordinate system. The $K - 1$ consecutive radar positions are estimated by dead reckoning as it is shown in Fig. 10.

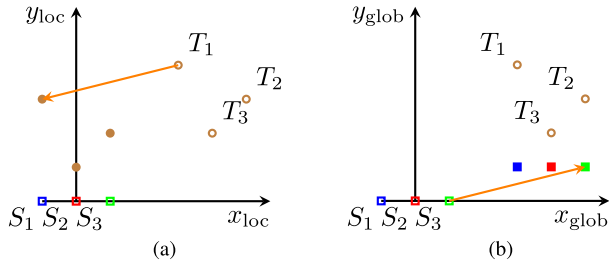


Fig. 11. Depiction of three stationary targets (○) for different positions of the mobile platform (second index) in a local and global coordinate system for three nonstationary sensors (□, □, and □). Filled markers specify the second measurement, whereas nonfilled markers declare the first measurement. (a) Local coordinate system. (b) Global coordinate system.

The algorithm ensures a localization of the sensor based on unknown, self-estimated landmarks without using velocity information and Kalman filtering. The main advantages of the approach are the full independence of the duration of the measurement break and the ability to cope with nonlinear motions of the vehicle [23]. Furthermore, the use of a subset of reliable targets for self-localization guarantees a good joint imaging due to the direct relation of the self-localized positions and the imaged scene.

A. Self-Localization

The target localization provides only the positions of the targets relative to the sensors but not in a global coordinate system. An exemplary scenario is shown in Fig. 11. Here, the shift of all targets in the local coordinate system between two consecutive measurements features a negative shift of the sensors in the global coordinate system. This is true as long as all stationary targets are matched correctly in the consecutive measurements. Ideally, the shift between all targets can be calculated and subtracted from the local sensor position to estimate the current global sensor positions. In the presented scenario, some challenges need to be addressed [24], [25]. First, the exact target positions are unknown but estimated based on multilateration. Furthermore, the same targets are not always detected in successive measurements, leading to a varying number of targets and, thus, a more complicated assignment. Together with the nonlinear uncertainty area caused by multilateration, this results in a more complex solution for localization.

To this end, an iterative localization approach for multiple chirp-sequence measurements has been developed. The basic algorithm structure is based on the minimization of an error function P . The minimization variables are the position of the mobile platform and the target locations based on the nonideal local multilateration approach. Due to a mechanical connection of the sensors, the position of each sensor is known with respect to a reference point in the local coordinate system in accordance with Fig. 1. The group of N sensors in the network for the time of a chirp-sequence measurement is referred to as single sequence measurement, whereas the consecutive chirp-sequence measurements during motion are described as multi-sequence measurements.

The error function P is based on multilateration. The estimation of the position of the mobile platform after at least two single sequence measurements makes use of the stationary

targets of the previous measurement together with the target detections of the current one. For instance, the error function for a two consecutive chirp-sequence measurements ($l_s = 2$) is given to

$$P(X, Y, S_{\text{pos}}, l_s) = \sum_{m=1}^{M_d} \left[\sum_{n=1}^N \left[\left((X_m - S_{\text{pos}}(n, 1, l_s))^2 + (Y_m - S_{\text{pos}}(n, 2, l_s))^2 \right)^{\frac{1}{2}} - S_{R,s}(n, m, l_s) \right]^2 \right]^2 \quad (4)$$

with X and Y being the vectors of the already estimated target positions. S_{pos} specifies the sensor positions as a matrix with the dimension $N \times 2 \times L$, where L describes the number of measured chirp sequences. The second dimension describes the x - and y -components of the positions of the sensors. l_s is the number of the last conducted chirp-sequence measurements and $S_{R,s}$ contains the range measurements of all sensors. This function calculates the difference between all sensor-target range measurements and all theoretical sensor-target distances for an arbitrary second position based on the first position of the mobile platform. The comparison between the measured distance and the real distance to all targets corresponds to the basic idea of a matched-filter approach. By minimizing this function for all possible platform positions, the most probable position is estimated.

The most accurate results can be achieved by an optimization over all chirp-sequence measurements and all targets that are measured along the trajectory. This approach has the disadvantage of a fast growing computational effort for an increasing number of measurements. By reducing the number of measurements, the results deteriorate, and inaccuracies due to offsets can occur. Therefore, an algorithm is used, which reaches a faster computation without reducing the localization accuracy. The main components are two different optimization states, which are the active (q) and passive (p) chirp-sequence measurements. The locations of active single sequence measurements are still optimized in the current optimization step. In contrast, the single sequence measurements that have a passive state are part of the optimization, but their locations in the global coordinate system are already fixed. In order to prevent offset shifting, the number of passive single sequences $p \geq 1$ is considered to ensure a permanent link to early localized targets and sensors.

The current single sequence measurement position i is optimized together with all q active previous measurements. Hence, the locations of q active measurements are optimized based on targets and sensor locations of the measurements $i - (q + 1)$ up to $i - (q + p)$. Using (4), the error function Q that has to be minimized can be written as

$$Q(X, Y, S_{\text{pos}}, l_s) = \sum_{B_q=i_s+1-q}^{l_s} [P(X, Y, S_{\text{pos}}, B_q)] + \sum_{B_p=l_s+1-q-p}^{l_s+1-q-1} [P(X, Y, S_{\text{pos}}, B_p)]. \quad (5)$$

The error function Q is separated into two similar parts, the part of the active sensors and the part of the passive

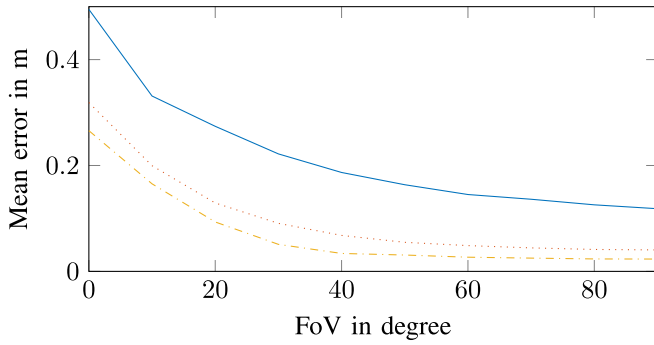


Fig. 12. Monte Carlo simulation shows the average self-localization error in meter for four sensors and a varying number of targets [two targets (—), five targets (·····), and ten targets (---)] for different FoVs. Targets are randomly distributed in a range between 5 and 50 m.

sensors. It specifies the distances between the measured radial velocities and the estimated global target positions as well as the global sensor positions. This is in accordance with a global multilateration approach. The minimization of the function for a measurement frame takes approximately 15 s without linearization. It results in accuracies smaller than 3 cm for the sensor positions at the time of the first transmitted FMCW ramp of each transmitted chirp sequence. Combining this information with the already estimated ego-motion leads to an entire trajectory estimation for arbitrary movements. Therefore, the locations of all measurements are precisely known at the time of the measurement and can be used for a multisnapshot imaging.

The accuracy of the trajectory of a given sensor setup strongly depends on the number and placement of the targets in a scenario. The estimation of the trajectory is only possible if suitable targets are detected. The distribution over a large angular range is particularly important, as can be observed in Fig. 12. The figure shows the simulation results for different FoVs and target numbers using the same parameters as used for the measurements. Each data point shows the mean error resulting from a large sample of randomly distributed targets. The strong improvement for large FoVs can be attributed to the larger angular differences between each sensor and a target. This improves the target localization by multilateration. Furthermore, the ego-motion estimation benefits from targets with large relative velocities, which is given for large FoVs. The simulation results also indicate a lower bound of the mean error that is caused by other factors, such as the radars range and velocity separability and the separation of the sensors.

In general, large sensor distances are advantageous and usually limited by the dimensions of the vehicle. On the one hand, larger differences in a target AoA have a positive effect on the multilateration and on the other hand also on the relative Doppler measurement. However, increasing the sensor spacing also reduces the overlapping FoV when the single-sensor FoVs are kept constant.

B. Imaging

For the exemplary measurement, the known trajectory in combination with the backprojection algorithm results in the SAR image, as shown in Fig. 14.

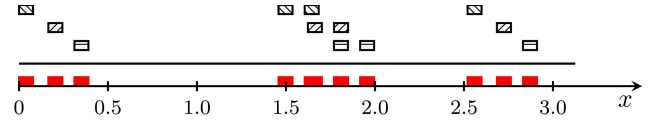


Fig. 13. Representation of the resulting synthetic aperture (■) comprising three consecutive single sequence measurements (■, ■, ■) for the used $N = 4$ sensors. The x -axis is scaled in meter.

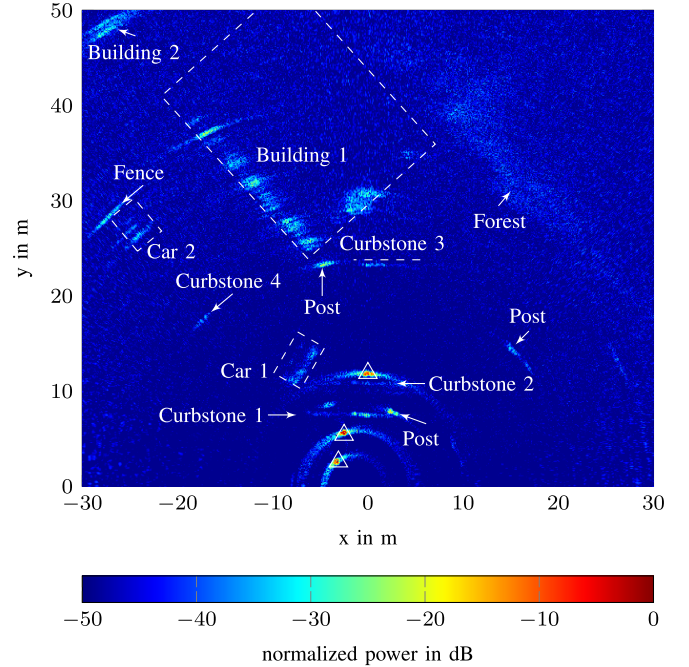


Fig. 14. Image comprising the data of all four sensors and ten measurements.

The entire synthetic aperture has a length of 5.6 m. For a total length of 1.4 m of this synthetic aperture, measurements are performed with a spacing less than $\lambda/2$ to satisfy the Nyquist criterion, but spatial sampling gaps remain due to a nonoptimal matching of the platform movement and the radars spatial sampling. In comparison to the processed image of a single sequence with four sensors (see Fig. 8), a significant improvement is achieved. The clutter level is reduced, and the contours of the forest and the buildings are clearly visible. Additional targets such as posts can be identified clearly as well as curbstone 3, which is detectable between $x = 0$ m and $x = 5$ m. This is a result of the extended synthetic multi-sequence aperture (■), which is shown in Fig. 13 for the first three chirp sequences (■, ■, and ■).

The summation of all multisensor measurements results in a multi-sequence image with slightly broadened peaks for the corner reflectors, as shown in Fig. 14, in comparison with the single sequence images as shown in Figs. 5 and 8. This is due to the estimation error of the global start positions of the single sequence within the multi-sequence measurement. A beneficial summation of multiple sequences is achieved, although the estimation error can be more than 20 times larger than the previously mentioned accuracy that is required for SAR processing.

Therefore, corner reflectors are slightly poorer focused on the image as shown in Fig. 14, resulting from the proposed multi-sequence processing compared with Figs. 5 and 8.

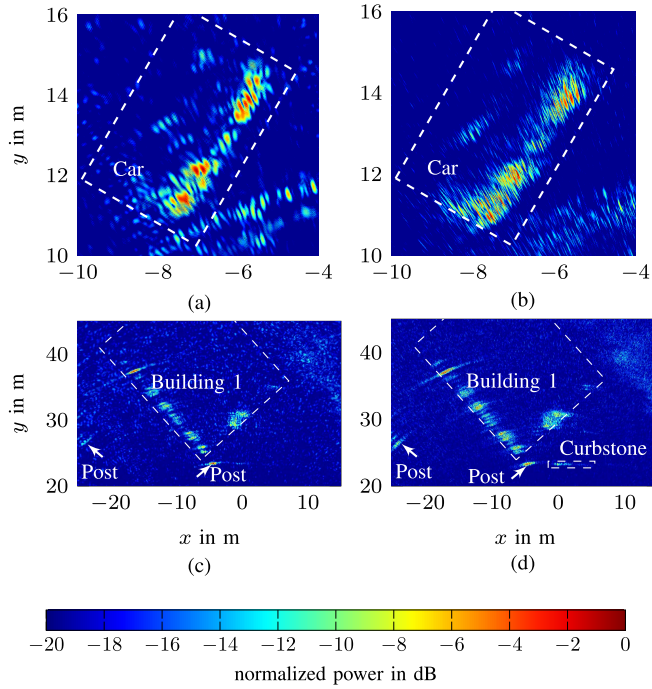


Fig. 15. Comparison of the SAR images based on the measurements of multiple sensors over two and ten chirp sequences. (a) Car 1, two sequences. (b) Car 1, ten sequences. (c) Building 1, two sequences. (d) Building 1, ten sequences.

This is due to the dead reckoning localization during the short movement in a single sequence. However, the simple approach serves as a proof of concept as the multi-sequence imaging allows to increase the imaged area significantly. Furthermore, the different view perspectives on a target add informational content to the image and thus support higher level algorithms, such as contour estimation and object classification [26]. Especially, the visibility of objects with strongly angle-dependent reflection behaviors benefits from the multi-sequence processing. For instance, Fig. 14 shows additional objects such as a post and much clearer contours of the curbstones. Furthermore, the comparison of images composed of two sequences and ten sequences in Fig. 15 shows a clear reduction of clutter for ten sequences. There is already an improvement visible between the single sequence images in Fig 9(b) and (d) and the images of two sequences in Fig. 15(a) and (c). An addition solely based on the amplitudes is shown in Fig. 16 for two and ten sequences. Here, an increased clutter level can be observed for the noncoherent addition in Fig. 16(b).

VI. ANALYSIS OF IMPAIRMENTS

Measurement inaccuracies, linear assumptions, and other simplifications lead to a reduced signal-to-clutter ratio of the SAR image. Sections VI-A and VI-B describe the impact of these assumptions on the two main error sources based on simulations: an incorrect ego-motion estimation and an accelerated motion.

A. Incorrect Ego-Motion Estimation

The quality of the SAR image corresponds directly to the position precision of the transmitter and receiver antennas at

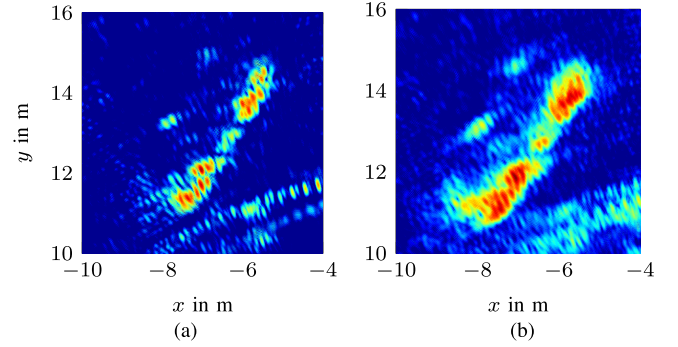


Fig. 16. Comparison of the noncoherent sequence addition-based SAR images. Evaluation of multiple sensors over two and ten chirp sequences. (a) Car 1, two sequences. (b) Car 1, ten sequences.

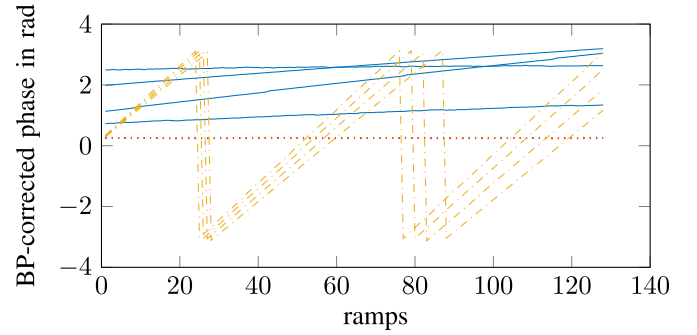


Fig. 17. Phase progression of a pixel over a single sequence after backprojection for the correct and incorrect speed assumptions. Four sensors are shown in each case. Depiction of the real target position using the correct sensor speed by dead reckoning (.....). In contrast, the resulting phase of a wrong speed assumption is shown for the real target position (---) and the pixel with the maximum power (—). Here, a speed deviation of 0.1 m/s is considered for dead reckoning.

the time of each transmitted FMCW ramp. This position is determined based on dead reckoning during a single sequence. Here, short-term fluctuations such as jitter that occurs during a single sequence are averaged out when the range-Doppler FFTs are evaluated. An incorrectly estimated ego-motion leads to monotonously deviating positions instead of randomly incorrect positions. This monotonously increasing deviation leads to two different effects.

First of all, the received signals will be incorrectly backprojected to the pixel grid. Therefore, a constructive interference of the signals at the real target position is not ensured. On the other hand, the monotonously increasing wrong sensor positions of the individual position of the moving platform shift the angles a target appears in. The phase progression of the corrected phase after application of the backprojection algorithm to all sensors for a specific pixel and a single sequence measurement is shown in Fig. 17 for three different cases:

- 1) real speed and real target position (.....);
- 2) wrong speed and real target position (---);
- 3) wrong speed and pixel with maximum power (—).

The simulation is based on the measurement system with four sensors. The phase progression over all FMCW ramps of a single sequence for four sensors is shown in each case. By evaluation of the real speed for the backprojection, the signal phases (see Fig. 17,) for all sensors and all ramps

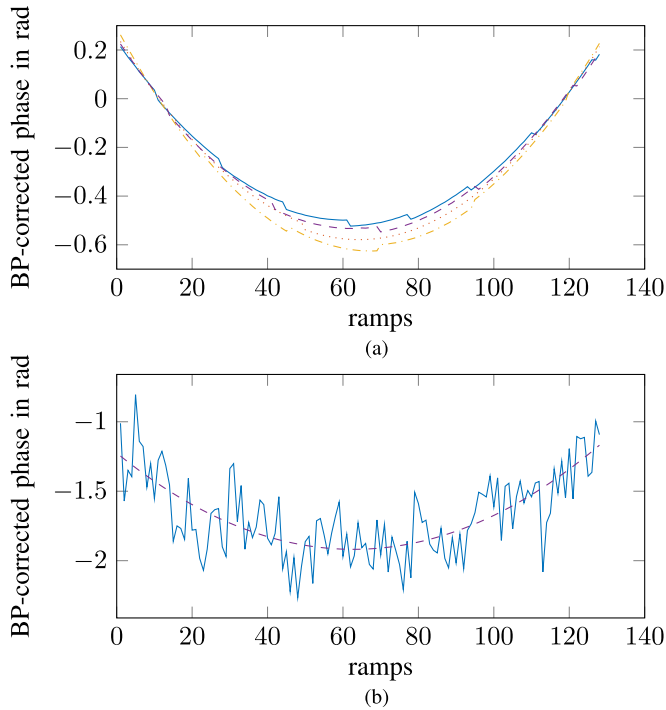


Fig. 18. Comparison of (a) simulation and (b) measurement during an acceleration of the mobile platform. The phase progression is depicted for a pixel of a real stationary target position after applying the backprojection algorithm. (a) Simulation with four sensors (—, ·····, ---, and - - -). (b) Measurement of one sensor during acceleration (—) and the corresponding quadratic regression (- - -).

are corrected in a way that leads to a constructive addition at the target locations. As soon as a velocity estimation error of 0.1 m/s is assumed, the signals no longer add up constructively but randomly at the real target position (see Fig. 17, ---), which is characterized as noise.

However, the synthetic aperture, which is small in relation to the target's distance, leads to a displacement of the target by 5° for this example. The phase progression of the pixel representing the most likely target position (see Fig. 17, ·····) based on the strongest amplitude is characterized by accurately corrected phases and only small deviations of a constant phase progression. Therefore, the addition of these signals leads to a power loss of only 3 dB, which means that a focused target can still be detected but at an incorrect angle.

B. Uniformly Accelerated Motion

In mobile applications, constant speed does not reflect reality due to acceleration, deceleration, and topological unevenness. Even small accelerations and slowdowns during a single sequence measurement have an effect on image processing. The actual effects depend on the length of the subaperture in relation to the change of speed. Hence, the signal phase of a target pixel is not constant after backprojection, if a constant speed is wrongly assumed. Here, the ego-motion estimation results in an averaged velocity of the motion during a single sequence measurement. The following SAR-processing is performed with partially incorrect sensor positions resulting in phase errors.

The influence on the SAR-image is shown in Fig. 18 for a measurement and a simulation with the same radar parameters for four sensors. Here, the signal phases after backprojection are depicted for a target pixel and all 128 ramps of a single sequence. The convex shape results from the wrongly assumed positions of the sensors due to the averaged ego-motion velocity used for dead reckoning. During the first half of the single sequence, the sensors move faster than the estimated velocity and slower during the second half of the sequence. The jagged pattern is caused by the range migration of the target. The measurement of an accelerated movement as shown in Fig. 18(b) shows a similar curve, but with more variations due to the dynamic driving behavior of the car during acceleration.

VII. CONCLUSION

The presented approach enables high-resolution radar imaging based on a network of conventional chirp-sequence radar sensors. The imaging is achieved by the use of the vehicle's motion in conjunction with the fast FMCW-ramp sequences. The approach does not require any additional sensors for motion estimation; instead, the ego-motion estimation is based on the same radar data as used for imaging. This enables a coherent SAR imaging with multiple sensors at a single snapshot. Measurements with four distributed radar sensors, resulting in subapertures of up to 64λ , show excellent results. In addition, a proof of concept for imaging among multiple measurement snapshots is presented. Here, the proposed approach improves the informational content of the images substantially.

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