GenRadar: Self-supervised Probabilistic Camera Synthesis based on Radar Frequencies

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Abstract—Autonomous systems require a continuous and dependable environment perception for navigation and decision-making, which is best achieved by combining different sensor types. Radar continues to function robustly in compromised circumstances in which cameras become impaired, guaranteeing a steady inflow of information. Yet, camera images provide a more intuitive and readily applicable impression of the world. This work combines the complementary strengths of both sensor types in a unique self-learning fusion approach for a probabilistic scene reconstruction in adverse surrounding conditions. After reducing the memory requirements of both high-dimensional measurements through a decoupled stochastic self-supervised compression technique, the proposed algorithm exploits similarities and establishes correspondences between both domains at different feature levels during training. Then, at inference time, relying exclusively on radio frequencies, the model successively predicts camera constituents in an autoregressive and self-contained process. These discrete tokens are finally transformed back into an instructive view of the respective surrounding, allowing to visually perceive potential dangers for important tasks downstream.

I. INTRODUCTION

A reliable and fail-safe capturing of the environment builds the foundation for many modern automatic applications like self-driving cars, robotic drones and diverse military purposes. Camera systems are omnipresent in this field nowadays, being cost-effective, easy to operate and their output readily interpretable in an intuitive way by either men or machine. Yet vision sensors tend to fail or at least their capabilities degrade in realistic circumstances featuring fog and snow or in poorly lit environments. [1]. It would be highly desirable to maintain a clear impression or at least a rough idea of the system’s vicinity, even within poor conditions to allow for a correct and responsible decision-making. Research so far has mostly focused on adding lidar sensors to improve sensing abilities through the inclusion of explicit range information. Conventional lidars, however, are similarly subjected to environmental influences and their performance breaks down drastically in harsh conditions [2]. Radar, due to its longer wavelengths largely unaffected by its surroundings, offers a powerful alternative for the enhancement of environment perceptions. This work therefore proposes a novel two-staged multi-modal fusion approach of both vision and microwave sensor data during neural network training. During inference, this allows for the probabilistic reconstruction and visual traceability of a scene’s central elements when only robust radar information is provided or available. Figure [1] gives an impression of the devised model’s scene-understanding, showcasing three randomly chosen examples taken from the test dataset, introduced in section II. To the present day, this work is one of only a few deep learning projects, dealing with the combination of camera and radar sensors [3], [4], [5], [6] and the first one demonstrating the fusion of their low-level data by means of completely annotation-free methods.

Algorithmically, the proposed procedure can be understood as an attempt to unify the respective strengths of two of the most ubiquitous neural architectures these days in a self-supervised manner, namely convolutional and transformers networks. Both models make specific but differing assumptions about the statistical composition of provided data and
have been used to great success in various research areas in which large quantities of data are to be processed to find patterns and concealed correlations.

Convolutional neural networks (CNNs) are predominantly used for computer vision tasks and represent the current state-of-the-art in this field. Presuming strong regional inter-pixel correlations, their specific architecture offers a feature called inductive bias allowing for the effective processing of image data, through small learnable filters which convolve across the input. In combination with weight-sharing among its many kernels and sub-sampling this makes convolutional layers approximately equivariant. Colloquially speaking, more importance is placed on the mere existence of certain information in the input rather than its precise location within. Their constrained receptive fields, however, allow CNNs to acquire higher-level features and identifying distant relations in the data only after the repeated stacking of numerous filters. This hierarchical structure is often necessary and sufficient for object detection tasks or semantic segmentation purposes, but may also hinder signal flow through the network if taken to an extreme. In this work, CNNs will be used in the first stage to derive effective modal-agnostic compression models. These learn to quantize the continuous high-dimensional measurements of both sensors into a stochastic and discrete number of constituents, summarizing their essential content.

Transformers in contrast, are specifically designed to model long-range interactions and find far-reaching concepts along the entire signal processing chain right from the start. The key ingredient to this ability lies within transformers self-attention mechanism, allowing them to capture global as well as local interaction between its sequential input alike. By stringing together multiple of these attention elements these architectures continue to achieve state-of-the-art results in many diverse fields of application. Their computational complexity, though, grows quadratically with sequence length, making them generally inapplicable for high-dimensional input. Operating on data streams of arbitrary length and with no prior knowledge about data’s inherent structuring included in their design, they rely on auxiliary positional information to help them encode notions of localization. This work relies on transformer architectures to establish cross-modal links and to compose environments in the stochastic latent space by learning distributions over discrete constituents. Decompressing the modeled sequences back into the continuous domain restores views of the sensors surroundings and allows to visually examine the implications of combining two complementary sensor types.

The main contributions of this submission are as follows:

1) Presentation of a versatile and comprehensive multimodal dataset featuring synchronized camera and low-level radar data capturing various real-world situations and traffic scenarios (section II-C).

2) Introduction of a novel method for compressing continuous sensor output into a stochastic sequence of integers via a consistent probabilistic self-supervised deep learning procedure (section II-A).

3) Derivation of a plausible and fully-probabilistic environment prediction through generation of RGB camera views based solely on streams of reliable and robust radio-frequency (RF) information (section III-B).

A. Sensor specifics and data representations

Radar while being a powerful and versatile sensor for many applications has not received quite as much attention as camera and lidar when it comes to the field of Deep Learning. This is partially due to its intricate parameterization and inherently complex data output which traditionally has to undergo numerous elaborate processing steps before being accessible to further case-related tasks downstream. Yet, radars key advantages cannot be excluded for much longer when it comes to automatic navigation and other areas in which a safety-critical environment perception is indispensable. Not only are radar sensors robust towards compromised lighting conditions or adverse weather influences (e.g. rain, fog or snow) they also allow for the direct and parallel measurement of radial distance and velocity of objects in its field of view. As such, they present a valuable asset to the familiar camera-based setup, bringing unique properties to the table that pure vision sensors are lacking. The most common representation of radar measurement results, employed within the field of autonomous driving, is in the form of discrete data points representing the positions of potential obstacles exemplified in red in Figure 2.

Each so-called target stands for one specific reflection center of the sensors transmitted electromagnetic wave and generally has further physical quantities inscribed: The radar cross-section (RCS) as a measure of the objects specific reflectivity characteristics and the associated relative radial velocity effectively resulting in a four-dimensional vector per point. This description is practical both in terms of intuition and data volume. Yet, it ignores a large amount of vital information which has been discarded along the signal processing chain by various assumptions, heuristic parameters and the algorithmic treatment altogether. This outflow of potentially crucial information is termed equivocation in information theory and commonly undesired yet in reality often times unavoidable, given constraints in both memory and compute. This work aims for reducing equivocation by drawing the data at an earlier stage, postulating that the preserved information may be of value for subsequent algorithmic tasks and procedures. In fact, the only processing the sensors raw voltage signals are subjected to are multidimensional Fourier transforms (cf. section II-C), mapping the time domain data into frequency plots as shown in Figure 2. The intensity distributions within these 1-channels images not only indicate locations and objects reflectivity. They also provide an immediate impression of approaching and removing targets by exploiting the Doppler effect. This allows to separate equidistant objects based on the slightest differences in movement illustrated by the two persons at a distance of 10 meters in the displayed measurement. The vertical center line at zero velocity includes static

1The term raw data is intentionally omitted due to its inconsistent use in both community and scientific literature.
objects at all distances, whereas the left and right image halves correspond to negative and positive radial velocities with respect to the sensor. This technique thus offers discriminative features, camera stills and their two-dimensional projections of the real world are missing. For although camera shots offer favorable lateral and vertical resolutions, they usually lack any depth information and computers still struggle with their extraction. Then again, these so-called range-Doppler (rD) maps really only carry meaning to humans either with associated axis labels detailing physical units or in combination with another synchronized sensor as in Figure 2. Apart from differential Doppler reflections of extended objects, no angular information is included in these specific plots, making them complex to read at first glance. Resorting to this rather pure form of radar data representation is justified though by the presumed existence of decisive information concealed within which are not to be missed due to premature noise assumptions and biased data cleansing. And although the memory demands necessary to store these data formats is magnitudes higher than those for sparse point clouds representations, the importance of the former cannot be overstated. Indeed, its significance is not to be assessed manually but should instead be evaluated by neural algorithms for which even the slightest preserved signal constituent might prove essential.

B. Foregoing explicit data annotations

Evidently, radar data at this level are both regularly structured and highly instructive and yet have not been given that much of attention within the machine learning community thus far. This can largely be explained by the difficulties touched on above but also because of the need for explicit annotations required for supervised learning — last decades dominant subfield within deep learning. Annotating radar signatures at any level is complicated due to its counterintuitive distribution patterns, especially if compared to camera and lidar sensor output. Additionally, multi-reflections and multi-path scattering as well as signal interference by electromagnetic radiation are just some of the effects frequently observed in spectral representations further contributing to their complexity. Annotation of radar point clouds most often relies on semi-automated labeling pipelines in which certain radar targets spatially coinciding with previously marked lidar points or camera frames are assigned the corresponding label. A human then attempts to correct wrongly classified points that inevitably result from imprecise calibrations and erroneous time-synchronizations. As an undesirable side effect, this introduces subjective judgment and individual bias into the data preparation, corrupting the purity of the data. This is further aggravated by the fact that reference camera stills commonly show occlusions or compromised views in adverse weather which leaves precise annotations up to guess-work and rough estimates. Manual intervention should therefore be abandoned or at least kept to a bare minimum. Labeling radar frequency plots, though, is a futile endeavor both in terms of time expenditure and data assessment. Making sense of abstract raw intensity maps is difficult and relating the many local maxima to traffic scenes based on associated camera footage appears to be virtually infeasible for even the simplest of situations. Still, recent years saw occasional publications of datasets, including annotated radar information in an attempt to close the gap to the other sensors for which multiple benchmarks have already existed for years. However, to simplify the described problems, those collections often feature only scarce amounts of radar data and labels given on discrete target-level [12], [13]. This turn necessitates particular methods like PointNets [14] for further processing. Some sets expose low sample rates and imbalanced object class distributions whereas other records do not include Doppler information [15], [16], depriving themselves of radars unique feature altogether. Only recently,
first radar datasets featuring annotations on the frequency level were made publicly available \cite{17, 18, 19} but it remains to be seen if these are going to have a similar impact on the community and will incite comparable research efforts as the famous KITTI \cite{20} and Cityscapes \cite{21} benchmarks did for vision-based scene understanding. Both aspects, the tedious annotation of radar data followed by an inevitable inflow of misinformation and the preferable elimination of equivocation call for completely different approaches, establishing the subfield of self-supervised learning. This domain dispenses with the traditional dependence on explicit labels and instead focuses on finding patterns and inherent structures within data by using parts of it as stimulus to supervise the remaining portion. It is suspected that self-supervised methods can exploit vastly more signals than conventional supervised learning approaches since the neural networks are no longer told what they are to infer. Rather, they have to find meaning in the input by themselves and construct high-dimensional feature vectors based only on the original data. Also, self-supervision encourages the algorithms to look for cross-correlations in multi-modal data in a more natural way, aligning nicely with the measurement setup used in this work. In fact, the feedback provided by low-level sensor output should be tremendous and surpass that of processed data records and explicit labels by large margins. As an additional appeal, unmarked data already exists or can be generated almost at will and with little cost. As such, self-supervised learning seems to be a natural fit for the regime of radar data in which labels are rare and hard to come by. Consequently, this publication delves into this field of mathematical and algorithmic intricacies in quite some detail, trying to take advantage of its full potential.

\subsection{Related Work}

In recent years, quite a few publications dealt with deep learning methods applied to radar data at various levels, aiming to expand the knowledge about the systems environment in one way or another. A first broad classification distinguishes between approaches on synthetic aperture radar (SAR) data whose image-like format is readily suitable to all sorts of pattern recognition models and continuous wave (CW) radar output, which is usually not immediately applicable for machine learning purposes. All projects can further be partitioned into supervised approaches which rely on explicit ground truths of some sort as described above and annotation-free methods which are most relevant to the present work. Among the latter are self-supervised techniques using little but the original radar data distributions to denoise micro-Doppler signatures, as shown in \cite{22} or enhance frequency plot resolutions demonstrated in \cite{23}. The authors construct a complex parameter fitting procedure that involves a Unet-like generator and patchGAN-reminiscent discriminator to tell apart clean and noisy spectra. To this end, they combine perceptual loss functions with a reconstruction criterion and perform adversarial training, learning to retain high-frequency details and remove unwanted artifacts. Ultimately, the authors advocate for resorting to neural algorithms for the outlined tasks as those arguably yield superior results compared to traditional thresholding or intensity correction schemes. A similar approach was followed by the authors in \cite{24} and \cite{25} where convolutional architectures are introduced for the purpose of reducing noise and interference in automotive radar spectra. CNN-based models are applied to the complex coefficients rather than their modulus at different stages along the signal processing chain. This allows to obtain a clear gain in information amount at the cost of added complexity and an increase in data volume. The devised neural approaches are input a combination of both real and simulated data for ease of retaining clean spectra for output comparison. Finally, those are benchmarked against conventional noise suppression techniques in an effort to demonstrate their benefits in terms of peak preservation and improvements in signal-to-noise ratio. Perhaps the work most related to this project has been described in \cite{26} by inferring human poses occluded by obstacles merely through Wi-Fi signals. In contrast to the above mentioned publications which perform intra-modal supervision, the authors present an approach which exploits time-synchronized camera data for supervision at train time in a teacher-student setup. This incites the network to acquire cross-modal correspondence features which, at test time, effectively allow for the sensing of human dynamics through walls and other barriers. This certainly raises some ethical questions, but also highlights the powerful nature and promising future of self-supervised systems without manual interference or exposure to human influence. All things considered, the previously addressed publications present strong arguments for self-supervised methods and underline the above stated claim of leaving the data alone and letting the neural structures decide for themselves which information to attend to the most.

\section{Data Collection and Sensor Settings}

The presented experiments were conducted on a custom dataset comprising roughly 50,000 samples of time-synchronized radar and camera images. The collection captures diverse real-world scenery around Ulm — Germany, varying in terms of both weather and lighting conditions. It features all kinds of realistic traffic scenarios ranging from clusters of pedestrians over lost-cargo situations and oncoming vehicles to the passing of trams and buses. The recordings were taken across the change of seasons during the course of one year to render them more versatile and expressive and to include a maximum of environmental diversity. A typical excerpt of the gathered data is shown in Figure 3 with more samples of both domains available at cditzel.github.io/GenRadar in detail and temporal succession. Both types of sensors were operated with a frame rate of 100 ms which was found to present a decent compromise between covering the intrinsic dynamics of outside scenes and limiting the amount of data to be stored. The entire multi-modal dataset was collected with an experimental stationary sensor setup to avoid having to compensate for ego-motions, which is no trivial task at the chosen data representation level. Also, no extrinsic calibration was performed prior to any recording, but both sensors were
spatially correlated by accurately aligning their horizontal field of views. This, however, does not prevent instances from being captured by one modality only due to different measurement ranges and aperture angles of both sensors. In fact, camera shots occasionally show distant objects in the lateral fringe areas turn up via frequencies but not in the camera. This renders the entire dataset quite realistic but also extremely complicated in terms of mutual correspondence learning. The assembly streams about 70 Mbit/s of RGB data and 40 Mbit/s of sampled RF data for a single enabled receive antenna so that about 14 MB were written to disk every second, emphasizing the extraordinary memory demands when working with low-level sensor data. Typical sequence lengths last from 10 s to 60 s capturing both short snippets and longer periods of random outdoor interactions.

A. Details on Radar Parameterization

The parameterization of chirp-sequence radars is notoriously complicated and involves the careful adjustment of several conflicting parameters which determine the maximum of both range and velocity as well as corresponding resolutions. Changing one parameter to improve e.g. the maximum detectable range often causes the acquisition of another measurement to deteriorate so that special care has to be taken to find some middle ground suitable for the task at hand. The MIMO-FMCW radar\(^2\) used to obtain the data for the present submission features a 77 GHz front-end and offers a multitude of configuration possibilities in terms of both signal modulation and data processing. The specific parameters selected for the gathering of this dataset are outlined in Table I for reference. Here only a brief abstract of the central sensor parameters, related physical quantities and measurement characteristics are given, crucial for the understanding of the data representations used in the following. For further information on how to derive the associated mathematical relations and working principles of a chirp-sequence radar as well as their interplay see \([27]\) and \([28]\). The concrete values for the numerous properties are of exemplary nature and represent a sensor configuration that was found to work reasonably well for the recording of the dataset without pushing the sensor to its limits. Starting from a carrier frequency \(f_c = 76 \text{ GHz}\) a directed electromagnetic wave is continuously emitted via a transmitting antenna, with its frequency being linearly modulated across a large bandwidth of \(f_{\text{BW}} = 1.5 \text{ GHz}\) during the sampling period \(T = 51.2 \mu\text{s}\). Fractions of this radiation are scattered by objects in the wave’s path and reflected back into the direction of the receive antennas, which collect the energy with certain delays due to round-trip times before converting it into a fluctuating voltages. Mixing both transmitted and received voltage signals (homodyne processing) followed by low-pass filtering results in a narrowband Intermediate Frequency (IF) signal with a bandwidth orders of magnitudes lower than the swept frequency range. The sampling rate of the Analog-to-Digital Converter (ADC) can thus be chosen to a moderate \(f_s = 10 \text{ MHz}\) capturing this time-series equidistantly with \(N = 512\) samples during every up-chirp period. The measuring process is illustrated in Figure 4 for an exemplary setup of two receive antennas. Due to the modulation, the individual frequency components that superimpose within this approximately sinusoidal IF-signal

\(^2\) RadarLog@www.inras.at

| Physical quantity | Acronym | Value | Unit |
|-------------------|---------|-------|------|
| Transmit power    | \(P_{\text{TX}}\) | 60    | mW   |
| Carrier frequency | \(f_c\) | 76    | GHz  |
| Wavelength        | \(\lambda\) | \(\sim 4\) | mm   |
| Bandwidth         | \(f_{\text{BW}}\) | 1.5   | GHz  |
| Sampling period   | \(T\)   | 51.2  | \(\mu\text{s}\) |
| Number of samples | \(N\)   | 512   |      |
| Sampling frequency| \(f_s\) | 10    | MHz  |
| Frequency resolution | \(\Delta f\) | 19.53 | kHz  |
| Sampling interval | \(\Delta t\) | 100   | ns   |
| Pulse repetition interval | \(T_{\text{PRI}}\) | 90    | \(\mu\text{s}\) |
| Pulse repetition frequency | \(f_p\) | 11.11 | kHz  |
| Coherent processing interval | \(T_{\text{CPI}}\) | 46.08 | ms   |
| Idle time         | \(T_{\text{IDL}}\) | 53.92 | ms   |
| Frame time        | \(T_{\text{FRM}}\) | 100   | ms   |
| Sensor frequency  | \(f_{\text{MEAS}}\) | 10    | Hz   |
| Center frequency  | \(f_0\) | 76.75 | GHz  |
| Max. Doppler frequency | \(f_D\) | 5.55  | kHz  |
| Number of chirps  | \(K\)   | 512   |      |

### Table I: Parameterization for chirp sequences of electromagnetic radiation.
The frequency modulation is of utmost importance as it allows to identify infinitesimal deviations within consecutive IF-signals. More precisely, sequences of multiple chirps taken in close succession exhibit small gradual phase shifts in case of relative movement between the electromagnetic source and objects in the wave’s path. Doppler frequencies quantify the rate of those phase changes and correspond linearly to respective relative velocities. The formerly detailed sampling process takes place within a frame time of \( T_{FRM} = 100 \text{ ms} \) which constitutes the sensor measuring frequency of \( f_{MEAS} = 10 \text{ Hz} \). The selected parameterization given in Table 1 defines the following measurement relations for the range dimension

\[
\Delta r = \frac{c}{2f_{BW}} = 0.1 \text{ m}
\]

and the velocity dimension in mutual interdependence

\[
\Delta v = \frac{\lambda}{2T_{CPI}} = \pm 0.042 \text{ m/s}
\]

\[
v_{\text{max}} = \frac{c}{4f_{0}}p_{\text{f}} = \frac{K\Delta v}{2} = \pm 10.8 \text{ m/s}.
\]

These quantities span a virtual uniform measurement grid with an extent of \( r_{\text{max}} \) in longitudinal and \( v_{\text{max}} \) in lateral direction limited by the sampling frequency \( f_{s} \) of the ADC and the pulse repetition frequency \( f_{p} = 1/T_{PRI} \) respectively. The coverage area is subjected to the Nyquist-Shannon bound so that targets beyond cause aliasing of the signal spectrum as well as ambiguous estimates for range, velocity or both. The range resolution \( \Delta r \) is the distance at which two targets are still marginally discernible, is dictated by the swept bandwidth of the frequency modulation. This entity effectively discretizes the range dimension into equidistant range gates so that multiple targets located within the same gate segment will be indistinguishable. The velocity resolution \( \Delta v \) is the minimum relative difference in speed between two equidistant targets that can be identified and defines the cell width in lateral direction. It can be enhanced by prolonging the continuous transmission time of the periodic signal \( T_{CPI} \), and thereby the entire duration of energy integration either through a larger number of chirps or a longer duration thereof. As a result, the velocity resolution depends largely on the modulation and can thus be increased almost arbitrarily. However, reducing the cell size for better resolution in either range or velocity shrinks the grid extent in the corresponding dimension and hence decreases the maximum range or velocity detection capability. The parameters in equation (1) to equation (4) therefore constitute a compromise between the accurate acquisition of discriminative Doppler and IF signals and a sufficiently large field of view to also capture distant real-world events. The total information accumulated by above design choices is written to file in the form of \( N \) discrete samples of the IF-signal for every consecutive chirp \( K \) yielding a 16 bit data matrix \( x_{IF} \in \mathbb{N}^{K \times N} \) for every chirp sequence within one recording.

**B. Details on Camera Parameterization**

The monocular camera footage was captured in unsigned 8-bit 3-channel RGB format with a resolution of \( x \in \mathbb{N}^{480 \times 640 \times 3} \) pixels and no further processing was applied prior to serialization. In particular, no steps were taken to reduce glaring reflections, blooming effects or to remove any imaging artifacts.

**C. Details on Radar Preprocessing**

The notion of imaging radar stems from the discretization described in section II-A and the structural resemblance of the data to natural images despite its vastly more abstract
and counterintuitive content. To extract the range and velocity information defined in equations (1) to (4) onto a regular grid, the de-serialized time-series undergo a number of frequency decomposition steps which are applied to each collated data matrix \( x_{IF} \in \mathbb{N}^{K \times N} \) of every frame under consideration. A single row of this matrix \( x_{IF}^n \in \mathbb{N}^N \) contains the entire intermediate frequency signal captured during one frequency burst. Successive columns \( x_{IF}^n \in \mathbb{N}^K \) represent individual samples taken at coinciding points in time within each sampling period across consecutive chirps. In line with the arguments given in Section I-A, processing of these matrices is kept to a minimum and merely involves finding the maxima of 2D spectra of the 1D time-series, representing the unknown differential and Doppler frequencies. According to mild requirements, formulated in [30], the optimal estimator of unknown frequencies within harmonic signals, observed during a finite time interval, are the maxima locations of the complex modulus applied to multidimensional Fourier spectra. The following steps are therefore performed in order and applied in parallel to the low-level data matrices.

1) A two-dimensional Hanning window is applied as trade-off between a decent side-lobe suppression and sufficient amplitude preservation in the frequency domain which comes at the expense of slightly broadened main lobes, see [30] for further details. This also reduces spectral leakage at the boundaries by mitigating the implicit assumption of infinitely-continuing signals included in the Fourier transform. The diminished signal peaks are later compensated for by appropriate window gain corrections to recover the signals true amplitudes.

2) An appropriate choice of zero-padding in both dimensions is made, which not only improves the granularity of the following frequency estimations, but also offers an opportunity to alter the resulting image extents as this modifies the frequency bin sizes which correspond to individual radar image pixels.

3) A Fast Fourier Transform [31] over the discrete samples of each chirp yields a matrix of complex coefficients \( x_{R} \in \mathbb{C}^{K \times (N/2+1)} \) with half the number of columns due to redundant spectral points mirrored along the Nyquist frequency \( f_s/2 \) for real-valued transforms. The elements in every row \( x_{R}^n \in \mathbb{C}^{N/2+1} \) now correspond to range bins (except for every first ones being the DC offset) and are multiplied by compensation factors to make up for window and transform-specific signal reductions. Taking the complex modulus, these values would immediately disclose radial distances to reflective obstacles reached by the electromagnetic wave within every chirp.

4) Additional Fourier transforms over the phasors along columns are tantamount to time derivatives of the aforementioned phase shifts across chirps. The matrix \( x_{RD} \in \mathbb{C}^{K \times (N/2+1)} \) then reveals unique Doppler frequencies for every range bin. These translate to signed radial velocities for possibly equidistant reflectors with varying speeds relative to the sensor. To restore the original signal peaks, these quantities are again compensated for due to the previous windowing. A subsequent shifting locates the zero-Doppler bin at the center of the frequency diagram. The graphical summary of this two-dimensional Fourier transform processing is illustrated in Figure 20 in the appendix.

5) What follows is the extraction of desired radial distances within a range of 1.3 to 25.6 m and Doppler information within the interval ±2.72 m/s via a submatrix \( x_{RD} \in \mathbb{C}^{256 \times 256} \). This choice respects the limits given by equations (2) and equation (4) and reduces the compute cycles of the upcoming neural operations considerably.

6) The computation of the power spectrum by squared modulus calculation of the complex coefficients ultimately results in a single-channel scalar-valued range-Doppler representation for every chirp sequence. A final log computation compresses the spectrum as it generally contains both very large and comparatively small entries and brings it to the more meaningful decibel scale \( x_{rad} = 20 \cdot \log_{10}(|x_{rad}|^2) \in \mathbb{R}^{256 \times 256} \). This becomes evident with regard to Figure 3 in which several maxima in the rD maps are allocated to the wheels of the vehicle or the extremities of the pedestrians. This observation serves as yet another justification for resorting to low-level radar data. Particularly the ability to discriminate structures via their Doppler spectrum proves powerful and informative for the following approaches. A limiting, but rather theoretical aspect in this regard is the implicit requirement that the radial velocity of all targets in the radar’s field of view is sufficiently low so as not to having them transition from one range bin to another during the course of one chirp sequence. Violation of this bound, called range-cell migration, impairs the accuracy of range and velocity estimates, most noticeable by spectral intensities being blurred-out across a number of rD cells. Figure 6 and Figure 7 report the radar intensity distributions of both train and validation set after the transformations. Prior to neural data processing, the frequency plots are transformed to the interval \( x_{rad} \in [-1, 1] \) to enhance training efficiency and diminish the impact of outliers in the datasets.

D. Details on Camera Preprocessing

The devised data processing pipeline loads batches of synchronized multi-modal records from disk in parallel, using them as input for the neural network training, described in subsequent chapters. Upon deserialization, the camera images are channel-wise re-scaled from \( x_{cam} \in [0, 255] \) to the interval \( x_{cam} \in [-1, 1] \) for this centering gives better conditioning of the numerical objective later on. As a next step, all data
are resized to $x_{\text{cam}} \in \mathbb{R}^{256 \times 256 \times 3}$ for all range-Doppler maps contained within the training dataset. The channel-wise pixel histograms of the entire collection are given in Figure 8 and Figure 9 alongside their cumulative distributions separated by train and validation split respectively. It is worth noting that no form of data cleansing is employed in any stage of signal preparation. In particular, no precautions are taken to guarantee the existence of central objects or salient features within every single multi-modal sample. Scenes may occasionally contain no dynamics at all, while other snippets are likely to show large groupings of moving individuals. This is to prevent the attention of the neural processing from becoming biased towards certain image regions and placing focus only on the most prominent parts within the input. Periodically, objects are clearly resolved in the camera image, while they are being lumped together in the corresponding rD map due to identical distances and similar velocities to the sensor. At other times, objects are clearly discernible through their reflections in the frequency plot but occluded in the camera image. Consequently, this dataset may be considered rather realistic, especially compared to the many polished benchmarks that exist nowadays. At the same time, this makes the presented algorithmic approach all the more challenging and hard to compare to existing methods. The entire dataset consisting of 50000 dual-domain samples was split into 43000 train samples, leaving recordings of 7000 samples for validation. Importantly, the division was done inter-sequentially, assigning only complete sequences to either set and not breaking recordings apart. It is expected, however, that this decision renders the entire task defined in section I much more difficult.
III. METHODOLOGY

The overall objective of explaining a captured radio-frequency spectrum through the probabilistic synthesis of an associated RGB camera image is ambitious due to the high-dimensional data of both domains. The most successful related approaches of deep conditional generations can thus far be found in the field of natural language processing. Here, byte-pair encoded words or fractions thereof are used, usually contained within finite-sized vocabularies. As sentences generally comprise only a small number of words, this drastically reduces the dimensionality of the problem, as predictions can only take on so many discrete possible outcomes. The situation is vastly different for natural images or spectral plots in which data points can take on a continuous, theoretically infinite range of values within certain intervals. Additionally, those forms of input notoriously exhibit a lot of noise and redundancies making it more difficult to extract relevant information. Consequently, previous image generation methods had to rely on massive amounts of computation power and restrict themselves to relatively small image sizes, as was done by the authors in [32]. Coping with the above challenges in a unique and seminal way was recently demonstrated by the work described in [33]. The authors successfully combined descriptive captions with associated compressed image components during autoregressive trainings in an attempt to render expressive, high-quality visuals based on content description in human language. Not only did they collect an unprecedented amount of image-text pairs, they also employed an unheard-of amount of compute to reach this goal. Moreover, they took advantage of the many tokenization schemes and predefined embeddings that exist for natural language processing and so had to discretize only one of two modalities, which they carried out in a all-encompassing probabilistic manner. More recently, a different group of researchers proved in [34] token-based image generation successful also for large-scale, high-resolution images if conditioned on a wide variety of accompanying visuals like depth images, semantic maps or salient objects within corresponding images. The authors had to come up with a way to jointly discretize two continuous high-dimensional modalities and decided on a deterministic vector quantization method [35] followed by a patchGAN-style discriminator downstream for further improvements in image construction quality. Another remarkable aspect of their report was the execution of their approach on a relatively modest hardware setup, especially if compared to the work of [33].

The present work follows along the steps of those projects but employs two physical measuring principles naturally related through the propagation of electromagnetic waves for information retrieval. The entire proposed algorithm comprises two disparate stages which are both trained end-to-end in a self-supervised fashion without the need for expensive and time-consuming annotations. In the first stage, RGB and RF data are probabilistically decomposed into separate discrete constituents in a holistic and mathematically-consistent way by means of an effective convolutional compression-decompression scheme described in section III-A. Both highly-compressed multi-modal data streams are then used in the second phase, to autoregressively train an attention-based model and stochastically predict camera-associated tokens conditioned on radio-frequency information as explained in section III-B. To this end, the holistic nature of the previous encoding process is abandoned and only the compression part is retained for discretization purposes. Upon successful sequence construction, the decompressor decodes the modeled integer series into a coherent and expressive camera view, relevant for several important use cases. Only after the training of both stages has been completed are predictions performed whose quality is assessed in section III-C in detail.

A. Probabilistic Discretization of the Latents

Variational autoencoders, short for VAEs, are a fundamental concept in the field of modern self-supervised learning. Originally introduced in [36] to perform variational inference and scalable expectation maximization [37] on large datasets, their convolutional counterparts have found their ways into numerous practical and scientific applications like representation learning and density estimation. As representatives of so-called directed generative models, they allow unconditional sampling of new data from a parametric approximation \( p_\theta(x) \) to the true underlying distribution \( p^*(x) \) which observations \( x \) are taken to originate from. Data-driven iterative maximum likelihood estimation (MLE) of the model parameters \( \theta \) causes the marginal approximation to successively converge to the unknown density so that

\[
p_\theta(x) \approx p^*(x) \quad \forall x \in \mathcal{X}.
\] (5)

Here, VAEs primary application will be the transformation of high-dimensional physical measurements into discrete low-dimensional equivalents. Also termed deep latent variable models, they are effectively used to perform variational inference over latent variables \( z \) assumed to be generating the observed data. The introduction of these latents increases model complexity and expressiveness so that the resulting joint distribution is capable of approximating even most complicated data collections

\[
\mathbb{E}_{x \sim p(x)} \left[ \log p_\theta(x) \right] = \mathbb{E}_{x \sim p(x)} \left[ \int_Z \log p_\theta(x, z) \, dz \right].
\] (6)

Maximizing this marginal log-likelihood is computationally intractable though which is why, using a parametric posterior distribution, the so-called variational lower bound (VLB) is optimized instead to approximate the model evidence above

\[
\arg \max_{\phi, \theta} \mathbb{E}_{x \sim p(x)} \sum_{z \sim q_\phi(z|x)} \log \frac{p_\theta(x, z)}{q_\phi(z|x)} \leq \mathbb{E}_{x \sim p(x)} \left[ \log p_\theta(x) \right].
\] (7)

Traditionally, Monte Carlo sampling and averaging replaces the calculation of the expectations. Within the context of
deep learning, this bound is usually decomposed into a reconstruction error and a regularization term forming the overall objective whose detailed derivation can be found in [38].

\[
L_{\phi, \theta}(x) = \mathbb{E}_{z \sim q_{\phi}(z | x)} \left[ \log p_{\theta}(x | z) \right] - \text{KL} \left( q_{\phi}(z | x) \parallel p(z) \right) \leq \log p_{\theta}(x) \tag{8}
\]

Above densities are parameterized by individual neural networks each with its own set of variational parameters \( \phi \) and \( \theta \) for joint optimization of this surrogate objective. Maximizing per sample-estimates of the VLB with stochastic gradient-based procedures then facilitates effective maximization of the evidence in end-to-end training. In the following section, the task-specific choices of the conditionals are established and assumptions on the distributions are justified which pave the way for an effective signal processing and the required quantization of the continuous measurement domains later on.

1) Theory About Categorical Variational Autoencoders:

The proposed compression approach necessitates the discretization of the latent space, preferably in a stochastic manner while forcing the latents at the same time to take on only a predefined range of values. Categorical variational autoencoders [59] are a special case of variational inference models described in the former section, most often used when a discrete probabilistic selection of features is desired, as in the present case. On an abstract level this architecture consists of an encoder and decoder part with a discrete stochastic bottleneck in between. The encoder network comprises a series of spatial downsampling convolutions with learnable filters defined by weights and biases \( \phi \). Transforming the input \( x \in \mathcal{X} \) into a discrete stochastic latent representation \( c \in \mathcal{C} \) of lower dimension forces it to learn an efficient compression by uncovering hidden concepts within the data. This Bayesian network is also called inference model [40] and is used to approximate the variational posterior in the VLB. In this context, it infers probability masses \( \pi \in \mathbb{R}^{N \times K} \) as nonlinear functions of the data where \( N = h \times w \) is the downsampled spatial extent of the input

\[
\pi = \text{encoder}_{\phi}(x) \quad x \overset{iid}{\sim} p(x). \tag{9}
\]

The encoder thus effectively parameterizes factorized \( K \)-categorical distributions over the \( N \) discrete latents collectively denoted as \( c \) henceforth

\[
q_{\phi}(c | x) = \prod_{i=1}^{N} q_{\phi}(c_i | x) = \prod_{i=1}^{N} \text{Cat}(c_i; \pi_i(x)). \tag{10}
\]

Relying on a technique called amortized inference, all categorical distributions over the \( N \) discrete latents collectively share the same set of variational parameters \( \phi \), yet, varying input induces different posterior conditionals. Every latent variable follows exactly one categorical distribution, which restricts the possible values, it can take on to a finite, potentially large number of discrete latent codes \( K = |\mathcal{C}| \). This aligns neatly with the proposed intention of deconstructing continuous data into related discrete representations located in a finite space \( \mathcal{C} \). In fact, various applications exist in which categorical latents are more suitable than their continuous counterpart, one of them being the subdivision of images into well-defined constituents that this work aims for. Following [41], the decision for a restricted number of possible outcomes of the sampling process allows to quantify the compression of the network from an information-theoretical point of view: According to Shannon’s source coding theorem [42], this choice defines an explicit upper bound \( \log K \) on the number of bits of information \( C \) can represent, an aspect which will be picked up again in the next paragraph. Discrete samples from the latent distributions in equation (10), representing square patches of the input image, are passed through the decoder, a sequence of learnable convolutional upsampling blocks governed by weights and biases \( \theta \) in an attempt to restore the original data as accurately as possible. This so-called generator approximates the likelihood in the VLB by mapping i.i.d. latents to corresponding mean vectors \( \mu \in \mathbb{R}^{M} \) with \( M = H \times W \times C \) of the input so that

\[
\mu = \text{decoder}_{\theta}(c) \quad c \sim q_{\phi}(c | x). \tag{11}
\]

The investigation of the data distributions detailed in section [41] allows for the simplifying assumption of pixel-wise independence with channel-wise fixed variance. This Bayesian model then induces spherical Gaussians in image space

\[
\log p_{\theta}(x | c) = \log \prod_{j=1}^{M} p_{\mu}(x_j | c) = \sum_{j=1}^{M} \log \mathcal{N}(x_j; \mu_j(c), \sigma^2) \tag{12}
\]

quantifying the information lost through transmission. Aside from concrete density choices and fuzzy latents, VAEs employ yet another regularization by introducing prior knowledge into their latent space, influencing the shape of the categorical posteriors and forcing samples to attain certain properties. Illustratively, these regularity constraints cause similar data points to end up close together in feature space, whereas the distance for dissimilar ones is increased. To this end, the divergence in equation (8) rewards proximity of the posterior \( q_{\phi}(c | x) \) to a task-specific existing belief \( p(c) \). Likewise, posterior distributions deviating too much from the specified priors, cause substantial perturbations of the overall objective. Seeking for an optimal exploitation of the entire code space \( \mathcal{C} \), fixed priors in the form of diffuse uniforms are chosen here in agreement with the relevant literature [43]. Following the notation in [37], these represent the maximum entropy configuration for the discrete case

\[
p(c) = \prod_{i=1}^{N} \text{Cat}(c_i; \pi_i) = \prod_{i=1}^{N} \prod_{k=1}^{K} \pi_{ik}, \quad \pi_{ik}^c = 1/K \tag{13}
\]

and recommend equal chance for every category to be selected. This imposes rather strict requirements on the latent space, but also helps in acquiring diverse and semantically meaningful features. These should eventually be able to efficiently decompose a large and versatile range of input into a set of well-defined constituents. On a more technical note, an
appropriate prior choice also mitigates the risk of posterior collapse, a phenomenon in which the model contents with relying on only a few fixed latents for data restoration. In this pathological case, described in [44] the categorical VAE would mimic a standard autoencoder with little stochastic characteristics. Although this might not affect its reconstruction abilities noticeably, it compromises the models expressiveness and generative potential profoundly. In view of the specific distributions defined above and with joint uniform priors in place, the VLB can be revised, offering further insights from an information-theoretical perspective. In particular, the divergence in expression (8) now disintegrates into Shannon’s entropy and an upper bound on the encoders compression capabilities as explained before

\[ \text{KL}[q_\phi(c | x) \parallel p(c)] = \mathbb{E}_{q_\phi(c | x)} \left[ \log q_\phi(c | x) - \log K^{-1} \right] = -\mathbb{H}[q_\phi(c | x)] + \log K. \]  

Both terms yield an estimate on the expected amount of information the model transmits about the data via its latents. Optimization of the variational bound thus involves maximizing both the likelihood and the conditional entropy of the categorical posterior bounded from above by a hyperparameter constant to be chosen a priori

\[ L_{\phi, \theta}(x) = \mathbb{E}_{c \sim q_\phi(c | x)} \left[ \log p_\theta(c | x) \right] + \beta \left( \mathbb{H}[q_\phi(c | x)] - \log K \right). \]  

An alternative interpretation is given in [45] as the divergence term being the expected amount of information necessary to convert an uninformned sample of \( p(c) \) into one from the approximated posterior \( q_\phi(c | x) \). For a posterior in equilibrium, i.e. exhibiting maximum entropy the divergence vanishes completely but the average number of bits required to communicate the state of its latent space reaches a maximum. Pertaining to the categorical model, a gain in entropy by striving for a uniform latent space utilization obstructs information flow through the network, essential for the overall reconstruction goal [37]. This contradiction of a more disentangled latent representation on one side and an optimal data restoration on the other is controlled by the introduction of an application-specific weighting parameter \( \beta > 0 \) in expression (15). Originally proposed in [46] this hyperparameter allows to subtly balance the relative tradeoff between both opposing terms in the VLB. Strictly speaking, the bound only holds for \( \beta = 1 \) recovering the original formulation. Yet, in practice, differing values have proven helpful to consolidate numerical convergence as demonstrated in later sections. In summary, the model now constitutes a mixture-of-Gaussians approximation to the marginal likelihood in equation (7). It features a categorical encoder mapping continuous input to parameters of discrete distributions that are drawn from once per latent variable during each forward pass of a single data sample. The decoder thus receives varying input in every iteration even for identical data points before transforming the latents into parameterized normal distributions over the continuous image space, rendering the entire training process probabilistic.

2) Declining Relaxation of Categorical Feature Selections: One of the strengths of modern neural networks is the effective approximation of high-dimensional functions by adapting millions or even billions of parameters through repetitive iterations over large datasets. After running a randomly taken subset of data through the directed graph, deviations from the respective objective are propagated back in reverse direction to adjust the networks weights via gradient updates for a lower error value in the next pass. Stochastic gradient descent algorithms are usually employed to fit the networks complexity to the respective data via batch-wise estimates of the negative likelihood. With regard to the model presented in the previous section, data-based optimization of the VLB should follow this same efficient procedure. However, changes in entropy require passing gradients of sampled entities back to the inference network. This poses a problem since it is not possible to back-propagate through stochastic nodes in computational graphs let alone through points at which discrete sampling took place. Various solutions to this issue have been proposed over the years, described at length in the literature [47], [48] alongside their respective characteristics. The method employed in this work relies on a smooth relaxation of the categoricals during the course of the data-fitting process by replacing the discrete samples with continuous approximations from so-called concrete distributions. Instead of drawing from true categoricals parameterized by the approximate posterior

\[ c \sim \text{Cat}(c; \pi_\phi(x)) = q_\phi(c | x), \quad c \in \mathbb{N}^N \]  

a vector-valued proxy sample is taken from a Gumbel-Softmax distribution for every of the \( N \) latent variables

\[ \tilde{c}_i = \text{GS}(\tilde{c}_i; \pi_{\phi_i}(x), \gamma_i, \tau) \quad \gamma_i \sim \text{Gumbel}(0, 1) \]  

with every component of the vector \( \tilde{c}_i \in \mathbb{R}^K \) calculated by

\[ \tilde{c}_{il} = \frac{\exp \left( (\log \pi_{\phi_i} + \gamma_i) / \tau \right)}{\sum_{k} \exp \left( (\log \pi_{\phi_{ik}} + \gamma_{ik}) / \tau \right)}, \quad l, k = 1, \ldots, K. \]  

Lower indices \( l \) and \( k \) denote categories now and \( \tau > 0 \) designates a temperature hyperparameter whereas \( \log \pi_{\phi_i} \) are the encoder logits which are interpreted as unnormalized log-probability of each category. This transformation provides well-defined gradients of the concrete distribution with respect to the parameters of the encoders final layer. In fact, it can be considered a variant of the reparameterization trick proposed in [36] which turns sampling of the latents into a deterministic function of the encoders logits and some independent additive noise from a predetermined distribution. For the discrete case, these perturbations \( \gamma_i \) in equation (17) follow a standard Gumbel distribution [49] allowing their efficient calculation via a standard uniform

\[ \gamma_i = -\log(-\log(u_i)) \quad u_i \sim \text{Unif}(0, 1) \]  

inserting stochastic properties into the learning process.
Concrete distribution

\[ \nabla_{\phi} L \]

\[ \exp \left( \frac{x_i}{\tau} \right) \sum_k \exp \left( \frac{x_k}{\tau} \right) \]

\[ \left[ \log \pi_1, \log \pi_2, \log \pi_3, \ldots, \log \pi_K \right] \sim \text{Gumbel} \]

\[ \gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_K \]

\[ \nabla_{\theta} L_{\phi, \theta}(x) \simeq \nabla_{\theta} \log p_{\theta}(x \mid \hat{c}) - \nabla_{\phi} \log q_{\phi}(\hat{c} \mid x). \quad (20) \]

Fig. 10. Gradient flow through the sampling process after Gumbel-Softmax reparameterization. The introduction of a temperature parameter and the addition of perturbation noise leads to pseudo-categorical latent variables with well-defined gradients. Errors can therefore be back-propagated to the encoder model, allowing efficient end-to-end training of the corresponding neural network.

without having to differentiate through the sampling itself. Gradients only flow along the re-parameterized deterministic nodes of the feature selection, see Figure 10 so that the VLB can be optimized w.r.t the inference networks parameters by

\[ \nabla_{\phi} L_{\phi, \theta}(x) \simeq \nabla_{\phi} \log p_{\theta}(x \mid \hat{c}) - \nabla_{\phi} \log q_{\phi}(\hat{c} \mid x). \quad (20) \]

This kind of expressions are referred to as Stochastic Gradient Variational Bayes (SGVB) estimators in the literature [40] and in this case produce biased gradients for the parameter adaption for reasons explained in the following. Gumbel-Softmax distributions were introduced simultaneously in [50] and [51] as an extension to the Gumbel-Max trick proposed in [52] to consistently sample from discrete distributions during end-to-end training of neural networks via backpropagation. The differentiable softmax function replaces the argmax operation used in [52] while maintaining the parameterizations relative ordering. Not only does it application normalize the raw logits, it also provides a soft approximation to the true categorical distribution without ever yielding one-hot samples exactly. Consequently, for temperatures \( \tau \in \mathbb{R}^+ \), the expectation of the concrete distribution never exactly matches that of the categorical actually sought after. The deviation between both and thereby the approximation quality is controlled by adjusting the temperature accordingly. Technically, this allows balancing the bias-variance tradeoff between the gradient estimates of taken samples. Larger temperatures emphasize the samples’ bias while reducing their variance due to higher entropies, causing the distributions to become increasingly uniform. And although this complies with the prior choice and has been reported to improve training robustness, it also hinders the encoder from moving towards outputting the desired categorical distributions. For lower temperature values close to zero, the one-hot encoding nature of the distributions is more accentuated as they converge towards true categoricals. The gradient estimates become more unbiased, but their variance increases, which generally disturbs the updating steps of the associated parameters and thereby the overall learning process. Choosing an appropriate \( \tau \) is thus a complex task and the authors in [50] recommend to either learn its value or anneal a prefixed one according to a predefined schedule which is what has been done in the current work as described in section III-A4. The gradients of equation (15) w.r.t. the generators variational parameters are calculated by Monte Carlo estimates of the batch-wise conditional likelihood with latent samples taken from the pseudo-categorical approximate posterior in the center of the graph during each forward pass.

\[ \nabla_{\theta} L_{\phi, \theta}(x) \simeq \nabla_{\theta} \log p_{\theta}(x \mid \hat{c}) \quad \hat{c} \sim q_{\phi}(\hat{c} \mid x). \quad (21) \]

3) Implementation Details of the Categorical Autoencoders:

Even though a wide range of autoencoder architectures exist both in theory and code and despite the fact that weights of numerous well-known networks are readily available for download and deployment in frameworks like [54], the specific data used in this project necessitate custom training. Most backbones are typically pre-trained on purified and cleansed benchmarks rather than realistic, application-oriented datasets which renders them unsuitable for the current project as their output lacks reconstruction quality or shows severe distortions if supplied with input described in section III. Moreover, the categorical bottleneck III-A2 and design choices tailored to the presented use case and given in the remainder of this section require training vanilla categorical VAEs for each modality from scratch. Figure 11 illustrates the concrete autoencoder architecture employed in the first stage of this work. Both inference and generator networks are fully-convolutional [55] seeking to exploit the immanent advantages of those models discussed in the beginning. The nonlinearities are ReLU activation functions [56] following every of the four down- and upsampling operations, respectively. In view of the data-specific distributions the decoder is to model, biases of all convolutional layers were preemptively disabled so as to prevent the model from solely learning a constant mapping from input to respective means as is warned against in [57]. The stochastic network maintains a constant number of 256 kernels per filter throughout, with a kernel size of four and deliberately foregoes pooling layers in the encoder in favor of double-strided convolutions with same padding. Pooling operations are notorious for preserving predominantly low frequency information while neglecting fine-grained details [58]. Retaining high-frequency content was argued to be essential though for reasons outlined on numerous occasions in this paper so that there exists genuine interest to not dispose of them by careless design decisions from the outset. Batch normalization [59], although still ubiquitous in modern deep learning, was dispensed with too, as was any other normalization method ordinarily included in most architectures. Though often shown to improve training
stability and accelerating convergence rates during training, batch normalization is prone to introduce peculiar dependencies of results on chosen batch sizes and data distributions. Every so often, this leads to unfavorable mismatches between training and validation runs due to inconsistent feature scaling in both phases. As a positive side effect, doing away with norm layers limits the total number of parameters to be optimized. Instead, normalization of the data is performed prior to network fitting by rescaling and recentering the data points according to their underlying modalities as described in sections II-C and II-D respectively. Additional pre-activation residual blocks with pure skip connections [60] are inserted immediately before and after the variational bottleneck to efficiently further information transmission to the posterior parameterization. These are succeeded by scaling $1 \times 1$ convolutions to bring the latent features in agreement with the desired number of categories $K$. The final logits $\pi$ of the inference network parameterize $N = h \times w = 16 \times 16 = 256$ categorical distributions per data sample over a single common learnable dictionary $\mathcal{E} \in \mathbb{R}^{K \times D}$ prepended to the generator. Latent samples then look up specific entries of this data-adaptable embedding, comparing them for semantic similarity during the learning process. Subsequent convolutions with a receptive field of $1 \times 1$ spatially aligns the vocabularies feature dimension $D$, with the decoder blocks in a computationally efficient manner. Since recent investigation suggests that generators too powerful have the potential of approaching the data distribution by ignoring the majority of latents and the prior conditioning [61], the decoder mirrors the encoder architecture as closely as possible and with modest complexity. In terms of reconstruction quality, no substantial difference was found between using either transposed convolutions [62] or upsampling followed by regular convolutions. The infamous checkerboard artifacts [63] frequently observed when using transposed convolutions were of little concern here due to quadratic kernel sizes of four being an integer multiple of the stride. A final convolutional layer transforms the last block of feature maps into 3- and 1-channel output of original spatial extent, modeling the pixel means for camera and radar input, respectively. The Gaussian assumption on those pixel distributions of both domains with unitary covariance as defined by equation (12), makes the reconstruction term in the VLB proportional to the expected mean squared error under the decoder model $\log p(x | \hat{c}) \propto \frac{1}{2\sigma^2} \| x - \mu_\theta(\hat{c}) \|^2$ [64]. A different choice for the distribution of the observation model in form of yet another categorical over the discrete pixel space was suggested in [65]. This was decided against here for two reasons: First, calculation of the corresponding cross-entropy loss requires an output channel number equal to the number of possible pixel values and thus significantly increases both model size and parameter space. Second, while the range of quantized integers for the unscaled camera data is known, radar spectra can assume largely varying values in a highly dynamic range depending on various factors, as stated in [11C]. Even if the value range could be specified a priori, subsequently casting continuous frequency points into integers would discard valuable information and hence stands in stark contrast to the arguments presented in chapter II.
4) Acquisition of Modal-Specific Probabilistic Dictionaries:

The primary reason for compressing both modalities into integer sequences is to reduce the memory footprint and compute requirements of the transformer model detailed in section III-B. For this purpose, the original images $x_{cam} \in \mathbb{R}^{H \times W \times 3}$ and $x_{rad} \in \mathbb{R}^{H \times W}$ are downsampled by a factor of 16 while passing through the encoder part of the network, yielding compression ratios of 768 and 256 for the camera and radar domain respectively upon discretization. This might seem to contradict the initially stated goal of preserving a maximum of information but rather substantiates the argument of giving the network the freedom to decide which information to keep and which to discard by adjusting its kernel weights. As such, this drastic compression approach is a tradeoff between information preservation and tenable computation effort with regard to the attention mechanism to follow. At the same time, this underlines the relevance of having to acquire an expressive dictionary, able to translate quantized information into semantically meaningful learned vectors to be eventually decoded by the generator. Given the general design of the overall network structure, outlined in the former chapter, this procedure leaves two main adjustment options, namely the size of the vocabulary $K$ and the feature length $D$ of each associated independent embedding vector $e \in \mathbb{R}^{D}$. One of the experiments, detailed in the following, ablates the number of selectable image constituents $K$ as this integral quantity should have major influence on information conservation. Concretely, the dataset’s variability, apparent also in the spatially confined $16 \times 16$ partially overlapping patches of the input, is compressed into a single integer per such section. It is believed that too small of a number $K$ should give too little choice to represent image content, forcing the dictionary to forfeit discriminative power in its feature dimension. A larger number of categories, on the contrary, gives it more freedom to develop patch-specific feature characteristics and is therefore likely to offer sufficient flexibility for the retention of fine details. Concerning the length of the feature vectors the vocabulary encompasses, $D = 512$ is picked after carefully balancing out requirements in feature expressiveness and memory demands. The biased gradient estimator, described in section III-A2, is used, enabling error propagation through the probabilistic nodes of the computation graph at train time. During this phase, for every input data point, 256 concrete sample vectors $\tilde{c}_i \in \mathbb{R}^{K}$ are linearly but separately combined with the dictionary $E \in \mathbb{R}^{K \times D}$ along the categorical dimension $K$. Owing to the continuous relaxation strategy, this contraction is weighted according to the current output of the inference model and further influenced by noise and the current temperature. This in turn encourages the involvement of all latent categories, especially in early training, facilitates signal flow through the network and provides valuable feedback to the encoder. An initial temperature around $\tau = 1$ in combination with randomly initialized encoder parameters stimulates a more uniform exploitation of the dictionary. In this context, the posteriors probability mass functions (PMF), given by the encoder logits are an indicator for the attraction from each image patch to every vocabulary entry. By measuring proximity in feature space between logits and learnable dictionary vectors, the inference model serves as a classifier of sorts, distributing scores across the entire embedding. The softmax normalizes the logits promoting numerical robustness while avoiding having image constituents settling too early for certain vocabulary entries. Sampling Gumbel noise at the bottleneck as given by equation (17) has added the benefit of reducing the risk becoming stuck in local minima during the data-fitting process. Attempting to close the variational gap between VLB and true likelihood, requires $\tau \to 0$ monotonically so that every image patch in the dataset should eventually be assigned one unique category. Decreasing the temperature causes the encoder to become increasingly self-confident about the category each image section belongs to by shifting probability masses accordingly. Consequently, the temperature is slowly but steadily annealed from $\tau = 1$ in every training step $t$ according to

$$\tau = \max \left( 0.0625, \exp(\text{-}0.000015t) \right)$$

for the first 10 and 50 epochs for radar and camera input respectively. This schedule decreases the parameter exponentially until reaching a minimum value of $\tau = 0.0625$ gently converging concrete samples towards true categoricals at the expense of a larger variance in gradient estimation. Having reached the lowest temperature, it is assumed that the model has adjusted its weight sufficiently to not be thrown off guard by coarse gradient values, turning unstable in subsequent iterations. During the validation phase, taking place after every training epoch, the temperature is frozen at the current value. To assess the models reconstruction quality, both qualitatively and quantitatively, it is then passed test samples from the validation dataset. The encoders response $\hat{c} \in \mathbb{R}^{h \times w \times K}$ in the form of concrete samples with nonzero values for all elements is then contracted along the dictionary entries as is done within training steps. Additionally, as no differentiation is performed at test time, the mode of the encoder-parameterized distribution for every of the $N$ latent variables is selected

$$c_i = \arg \max_{k \in [1,K]} \pi_{\phi_k}(x), \quad i = 1, \ldots, N = h \times w$$

indicating where the bulk of the probability mass is currently located. To include genuine discrete sampling in the validation probing, the encoders output is also used to define $N$ true categoricals as a third alternative. Sampling these adds slight regularization and some degree of fuzziness to the selection of the probabilistic latents. Moreover, excluding the temperature influence allows to examine the impact of an increasingly confident encoder on the discretization and restoration capabilities of the model. The sample spaces for the last two index collections consist of finite integer sequences $s \in \mathbb{N}^N$ with $N = 256$ representing the compressed input image of the respective modality in raster order. Extracting these series of tokens lays the foundation for the sequence modeling in the second stage. Using them here for the discrete selection of reconstruction features gives an outlook on the
achievable image quality and serves as a visual upper bound to the autoregressive generation performed later on. Except for the concrete case, only individual embeddings $e \in \mathbb{R}^D$ are selected now by using the sampled integers to index into the corresponding domain-specific dictionary $\mathcal{E} \in \mathbb{R}^{K \times D}$. This allows to retrieve associated feature vectors which are hoped to have acquired some notion of context-awareness during the course of previous training. In doing so, the entire token sequence $s \in \mathbb{N}^N$ is transformed into a continuous latent equivalent $z \in \mathbb{R}^{N \times D}$. After reshaping into $z \in \mathbb{R}^{N \times W \times D}$ the decoder reconstruction begins to reduce the feature dimension while concurrently upsampling spatial dimensions. In theory, at convergence of the data-fitting process, only subtle differences between the three different token sets and their visual restorations should remain: Upon training termination, the encoder should have gained the competence to unambiguously classify subimages into one of many categories, while the low temperature effectively turns sampling from the Gumbel-Softmax distribution into nearly discrete operations with only minor deviations due to the influence of Gumbel noise. Optimizing the models objective in equation (15) involves the opposing goals of increasing the entropy with respect to $\phi$ while raising the lower bound in terms of $\theta$ to maximize the data likelihood. To mitigate this tradeoff fixed values $\beta_{\text{cam}} = 5 \times 10^{-4}$ and $\beta_{\text{rad}} = 5 \times 10^{-5}$ were found for the data decompositions. Their magnitudes reflect to a certain degree the estimated per-sample difference in content relevance between both modalities and are combined with the inverse compression ratios $\beta = \beta N / M$ with $N$ as the size of the latent space and $M$ as the number of input/output dimensions as before. It was found that these values allow to uphold the delicate balance between the contrasting objectives and provide for sufficiently structured latent spaces at the cost of slightly distorted reconstructions. Resorting to a dynamic schedule for this parameter, reported successful in [69], did not show any improvements for the present analysis. In fact, gradually increasing the divergence weight corrupted convergence from the very beginning, presumably due to conflicts with the temperature annealing. Minimizing the equivalent negative lower bound was performed by Adam [67] as the numerical solver of choice due to its reputation of being rather forgiving to suboptimal hyperparameter choices [68]. This also includes rough initial guesses on the learning rate, which was set to $3 \times 10^{-4}$ but reduced by half after every 10 validation epochs in which no overall loss reduction could be observed. Kaiming initialization of both sets of variational parameters $\phi$ and $\theta$ in the convolutional layers was done following [69] while the weights of the vocabulary were drawn from a uniform distribution. Separate models were trained for both modalities and all computations were run on single GeForce RTX 2080 Ti units with ~12 GB of RAM, using a maximum batch size of 24. Calculations were terminated after the validation loss stopped increasing for more than 20 epochs. The outlined probabilistic compression is a complex task as is, so no further data augmentation was used on either domain. Range-Doppler maps carry inherent meaning of various physical quantities which cropping or random resizing operations would destroy or at least severely impair. Specific intensity distributions immediately establish useful correspondences to the time-associated content of the camera frame and must not be tinkered with. For similar reasons, the frequency plots were not subjected to flipping of any kind, as this would reverse the velocity or range estimates included in the RF data. Likewise, stochastically mapping the camera footage to an accurate replica is difficult due to the diverse content and VAEs infamous tendency of imposing certain amounts of blurriness onto their output [40]. So no further processing was applied to the RGB data other than that described in section III.

5) Results and Discussion of Probabilistic Decompositions:

Evaluation of the implemented models is complicated because of the custom datasets and the novel intention-driven stochastic decomposition method of continuous domains. Traditional benchmarks do not apply to the specific case of radar frequency data, which is why ablation studies among different model configurations are performed to obtain an impression of their abilities. Also, no universally agreed-upon performance metrics for self-supervised learning in general exist as of today. This is particularly true for generative models and the quality of their synthesizing capabilities, whose evaluation is still an open research question. Over the years, many measures have been proposed without one of them ever exclusively taking prevalence over the others. Yet, certain approaches have proven helpful to examine the abilities of trained networks, at least to some extent. Here two methods are used, relying on similarities between original data and reconstructions in pixel and feature space, respectively. The first one assesses the quality with which models are mapping discrete stochastic latents back to the continuous domain by application of two metrics, the Frobenius norm and the peak signal-to-noise ratio between input and means output by the generators. Table IV to table VII show the results for both modalities, different vocabulary sizes and sampling methods. Additionally, the number of feature maps constant along the network architecture is ablated as this gives clear evidence on the necessity of sufficient complexity within the models for restoration quality. Since the Frobenius norm is only defined for matrices, it is calculated and averaged channel-wise for the camera images. The results are then averaged over the entire validation dataset and across three consecutive runs to reduce sampling noise. Also, the tables report the epoch number after which the iterations were deemed to having converged, i.e. after which no improvement in validation error occurred for more than ten epochs.

The depth of convolution blocks has vastly more impact on the metrics than the dictionary size. This is not surprising given this parameter’s linear influence on the number of weights the networks have at their disposal, determining their flexibility. As expected, the larger the number of possible latent categories, the better the general approximation quality. However, this parameter seems to entail only minor differences for both metrics across the entire validation set. A possible reason is that the collection features a lot of static backgrounds for the camera data and vast regions of noise for the radar input which
generally vary little from frame to frame and thus do not exert much influence on the pixel-wise comparisons. It is therefore imperative to evaluate the models’ validity with a different kind of measure which mimics human visual responses more realistically and might prove helpful in substantiating the tendencies apparent in the tables. This other method for measuring the faithfulness of generative models has been proposed by \cite{80} in form of the so-called Fréchet inception distance (FID) as an improvement over the Inception score (IS) \cite{71} widely used before. It evaluates the quality of generated images by determining their distance to the originals through higher-level features rather than pixel-wise. The rationale here is that feature embedding vectors are more likely to correspond to real-world objects and image constituents akin to how a human would perceive similarity and judge visual quality. To this end, both original and generated data are independently fed into the Inception-v3 model \cite{72} pretrained on the ImageNet \cite{73} dataset. Optimized to predict the contained 1000 object classes to high accuracy, this model serves as a feature extractor, effectively transforming high-dimensional images into a lower-dimensional latent space in which similar input should have a certain proximity. Tapping into its architecture after the last pooling layer allows to summarize its 2048 activations as multivariate Gaussians by fitting mean and covariance to the respective data distribution under consideration. The FID then is the Wasserstein distance between the corresponding first two statistical moments calculated over the entire validation dataset and three averaging runs on its probabilistic reconstructions

\[
\text{FID} = \| \mu_d - \mu_g \|_2^2 + \text{Tr} \left( \Sigma_d + \Sigma_g - 2 \left( \Sigma_d \Sigma_g \right)^{\frac{1}{2}} \right). \tag{24}
\]

The smaller this distance, the more related two datasets are and the finer the reconstruction quality is believed to be. Consequently this value vanishes for identical distributions. FID is far from an optimal measure as it reveals a strong bias towards the size of the datasets. It does, however, provide a more elaborate insight into the models inner workings and recognizes qualitative tendencies better than any other metric introduced so far as it represents the current state-of-the-art for the evaluation of generative models as of 2021. The FID for both modalities is depicted in Figure 12 as a function of dictionary size ablated once again over the channel depth of the networks. To bring the radar input into agreement with the first layers of the inception model, the RD maps were replicated thrice before feeding them into the network. Surprisingly, the plot shows non-monotonous graphs for some of the smaller network depths, but overall confirms the observations made before about the larger dictionaries being most potent regarding the maximization of the VLB objective. The metrics significance about the frequency plots remains questionable to say the least, but nonetheless offers an opportunity for intra-modal comparison. From here on out,

### Table II

| K | Mode | Categorical | Concrete | Depth | Epoch |
|---|------|-------------|----------|-------|-------|
| 64 | 19.40 | 19.41 ± 0.11 | 19.33 ± 0.02 | 64 | 122 |
| 16,54 | 15.69 ± 0.13 | 16.45 ± 0.05 | 128 | 141 |
| 13.59 | 13.64 ± 0.44 | 13.57 ± 0.08 | 256 | 68 |
| 256 | 18.88 | 18.87 ± 0.04 | 18.84 ± 0.02 | 64 | 156 |
| 15.77 | 15.77 ± 0.02 | 15.75 ± 0.04 | 128 | 146 |
| 13.43 | 13.44 ± 0.18 | 13.37 ± 0.15 | 256 | 59 |
| 1024 | 17.84 | 17.87 ± 0.22 | 17.72 ± 0.06 | 64 | 156 |
| 15.46 | 15.51 ± 0.20 | 15.42 ± 0.05 | 128 | 142 |
| 13.16 | 13.23 ± 0.14 | 13.17 ± 0.02 | 256 | 75 |

### Table III

| K | Mode | Categorical | Concrete | Depth | Epoch |
|---|------|-------------|----------|-------|-------|
| 64 | 23.39 | 23.42 ± 0.03 | 23.36 ± 0.05 | 64 | 49 |
| 23.30 | 23.33 ± 0.05 | 23.26 ± 0.04 | 128 | 36 |
| 23.41 | 23.42 ± 0.11 | 23.37 ± 0.03 | 256 | 24 |
| 256 | 25.90 | 24.25 ± 1.12 | 23.79 ± 0.03 | 64 | 15 |
| 29.78 | 25.35 ± 0.97 | 23.76 ± 0.29 | 128 | 6 |
| 23.22 | 23.25 ± 0.12 | 23.16 ± 0.03 | 256 | 51 |
| 1024 | 29.35 | 24.27 ± 0.03 | 23.69 ± 0.04 | 64 | 9 |
| 30.60 | 23.68 ± 0.05 | 25.03 ± 0.01 | 128 | 4 |
| 22.99 | 23.06 ± 0.06 | 22.95 ± 0.03 | 256 | 71 |

### Table IV

| K | Mode | Categorical | Concrete | Depth | Epoch |
|---|------|-------------|----------|-------|-------|
| 64 | 16.86 | 16.85 ± 0.01 | 16.89 ± 0.01 | 64 | 122 |
| 18.47 | 18.45 ± 0.06 | 18.53 ± 0.03 | 128 | 141 |
| 20.58 | 20.54 ± 0.04 | 20.58 ± 0.08 | 256 | 68 |
| 256 | 17.17 | 17.17 ± 0.05 | 17.17 ± 0.08 | 64 | 156 |
| 18.98 | 18.98 ± 0.01 | 18.99 ± 0.07 | 128 | 146 |
| 20.64 | 20.66 ± 0.02 | 20.73 ± 0.03 | 256 | 59 |
| 1024 | 17.66 | 17.64 ± 0.05 | 17.72 ± 0.01 | 64 | 156 |
| 19.17 | 19.13 ± 0.02 | 19.18 ± 0.01 | 128 | 142 |
| 20.94 | 20.87 ± 0.07 | 20.86 ± 0.03 | 256 | 75 |
only models with a kernel number of 256 will be used further as those undoubtedly produce the most favorable results. To obtain a comprehensive notion of the models’ versatility, their latent space utilization for a size of $K = |\mathcal{C}| = 256$ is recorded separately for every latent variable over the validation dataset. To yield a reproducible result, the modes of the data-induced PMF, given by equation (23), are accumulated for every input sample and displayed in Figure 29 for both domains. Pronounced vertical lines indicate frequent use for that particular category across many latent variables whereas less regular and interrupted structures speak for a more evenly utilized code space. The learned semantic concepts and acquired knowledge of the discretization models with $K = |\mathcal{C}| = 256$ can also be explored by querying each vocabulary entry exactly once and in increasing order before decoding the resultant continuous feature space, shown in Figure 13. To give a visual impression of the models’ variety, both generators were also probed for their acquired knowledge by successively selecting indices from $c = 1$ to $c = 256$ one at a time for all latents. Figure 28 in the appendix shows the results of successively decoding these identical categories into individual images. The more distinct these images, the more expressive the latent codes and the more effective the related discretization schemes are assumed to be. Likewise, a large number of similar looking patches points towards potential redundancies in the dictionary. A clear sign, that the model does not fully exploit the potential of the discrete code but instead has found convenient shortcuts to fulfill the objective during training. Additionally, Figure 25 and Figure 27 in the appendix show typical failed examples and degenerated modes experienced during various stochastic compression attempts. As pointed out before, training VAEs is a difficult trade and minor deviations from optimal hyperparameter choices can cause the learning to turn unstable. Concretely, in the first few iterations, the reconstruction term in the VLB has little impact on the overall loss. Approximate compliance of the posterior with the uniform prior can then represent a local equilibrium configuration from which the algorithm can have problems to escape. Successful validation results of selected model runs are displayed for completeness in Figure 21 in the appendix. Furthermore, Figure 22 to Figure 25 give visual impressions of the qualitative reconstruction differences between vocabulary sizes of 64 and 1024, respectively, alongside the normalized histograms of the utilized latent codes. It becomes evident that dictionaries of all sizes are able to stochastically decompose and reassemble diverse real-world data, albeit with varying level of detail. Especially camera content located in the far background can be reproduced significantly sharper with a greater dictionary. Concerning the crispness of rD maps, larger vocabularies clearly enable superior recovery of noise patterns and shape reproduction of complex intensity clusters. This is of vital importance, for ignorance about every single radar cell neglects all information within a $0.1 \, \text{m} \times \pm 0.02 \, \text{m/s}$ interval. As it turns out, accurately predicting additive noise, omnipresent in rD plots is extremely difficult, noticeable among other things in clear contrast differences between input and reconstructions. VAEs in general are known for inflicting a certain amount of blur onto their output which is clearly recognizable particularly with regard to dynamic objects or a certain amount of blur onto their output which is clearly recognizable particularly with regard to dynamic objects or the precise modeling of intensity pattern in radar input. The rationale for this is manifold: For one thing, the feature size and shape reproduction of complex intensity clusters. This is of vital importance, for ignorance about every single radar cell neglects all information within a $0.1 \, \text{m} \times \pm 0.02 \, \text{m/s}$ interval. As it turns out, accurately predicting additive noise, omnipresent in rD plots is extremely difficult, noticeable among other things in clear contrast differences between input and reconstructions. VAEs in general are known for inflicting a certain amount of blur onto their output which is clearly recognizable particularly with regard to dynamic objects or the precise modeling of intensity pattern in radar input. The rationale for this is manifold: For one thing, the feature size limits imposed on the bottleneck and the struggle of conforming to the prior while having the L2 criterion evaluating the output means leads to a decline in visual quality. Second, the model has seen multitudes of examples featuring the many backgrounds and large areas of noise whereas vulnerable road users (VRU), for example, have been presented to it only so many times and always in different poses and settings. Also, individuals or moving objects and reflections tend to occupy only small pixel regions of the images. Covering those more precisely, the model would have to allocate an individual category for each of these instances included in the dataset.
Given the limited number of tokens, the input can be split into, this makes it drastically harder for the network to accurately restore the remaining image parts. It is thus more likely that it chooses to represent dynamic elements and aggregated reflections as compositions of several discrete constituents instead, relying on the decoder to combine and assemble them correctly. To components, frequently present in images like skylines or road segments, the model probably dedicates separate categories, effectively using them as basic building blocks for the majority of image generations. Videos showcasing the specific restoration capabilities for exemplary scenes in a more vivid form can be found at cditzel.github.io/GenRadar.

As pointed out in chapter III the current approach depends on a versatile and expressive dictionary to unambiguously compress continuous-valued input into discrete sequences by preferably large margins in the decision process. As seen before, this is rather challenging, especially concerning the spectral plots with a lot of noise present across the entire depiction. Hence, the goal has to be inhibiting the model from assigning a single token repeatedly to radar patches which predominantly comprise noise. Enlarging the number of categories the models can choose from in the regularized latent space should make for enhanced disentanglement and better data representation of these discrete image parts. In other words, a more distinguished vocabulary makes for improved assignments of image patches to integers, thus aiding the reconstruction altogether. To examine this claim in more detail, the total amount of all possible information the models encode is investigated by calculating their perplexity. After a change to binary base, this can be expressed via entropy exponentiation

$$\text{perplexity}(q) = \prod_c q(c|x)^{-q(c|x)} = 2^{\mathbb{H}[q(c|x)]}.$$  \hspace{2cm} (25)

Figure 14 contrasts this variational entity of the camera with that of the radar models across consecutive validation runs performed after every training epoch. All measures are with regard to a single latent symbol facilitating the association with an actual number of bits required to transmit its state through the network. Figuratively speaking, perplexity measures the amount of randomness in the model and quantifies how well the associated process predicts samples. It calculates the weighted average number of choices each latent variable is offered. Referring to the categorical encoder introduced in section III-A1 this means, the higher the perplexity the more uniformly distributed the underlying stochastic selection of latent constituents is. Conversely, a lower number indicates that the model grows more confident at predicting the category an image patch should belong to. In view of Figure 14 this aligns with the formerly stated conflict about the VLB in equation 15. Making the bound approach the marginal likelihood demands a decrease in KL divergence during training, which can only be achieved by the posterior converging towards equilibrium. This raises the system’s entropy, but would make for a more homogeneous use of the dictionary at the expense of more bits necessary to represent the compression. For a lowest possible data-restoration error and likelihood maximization, less randomness of the feature choice is preferable, but alienates the categorical posterior from the prior, visible by a gain in KL-divergence. Though this generally reduces entropy and the number of bits required to communicate the latent state it involves the risk of ending up with only a small amount of effectively used codes. This does not necessarily show in the reconstruction quality, as the latent feature vectors might still attain a broad knowledge during the course of training but will certainly impede the autoregressive prediction, subject of the next section. The inverse relations between the described quantities are clearly recognizable by contrasting the first two rows of illustration 14. The noted
arguments underline the importance of finding a suitable combination of the divergence and temperature parameter which both exert major influence on the arrangement of the latent spaces. For reference, the plot also lists the effective perplexity for which discrete samples rather than distributions were taken as a basis for evaluation. Deviations between both measures of perplexity, particularly visible for the radar models, might be seen as a less confident feature selection process. One problem associated with perplexity in general is its dependence on the employed batch size. Therefore, also the actual bin count of the vocabulary histogram over one complete validation epoch is included in the graphs, giving a more reliable impression of the latent space exploitation. Differences in divergence weights and temperatures make a direct comparison between both modalities difficult. Interestingly though, the radar models generally seem to settle for more customized latent distributions and eventually, content with higher structured latent spaces. Referring to the practical dictionary usage, however, displays similar developments of the utilization than those of the camera models after stabilization past epoch 25. Further, the reconstructed pixel and intensity distributions for the final model selection is shown in Figure 15 in contrast to the dataset distributions previously given in Figure 7 and Figure 9 which are repeated here for convenience.

After having acquired stochastic compression models for both modalities, their holistic processing procedure is now abandoned by breaking apart the categorical autoencoders into the inference networks and the generators, including the adjusted upstream vocabularies. In the next chapter, the former ones will serve as tokenizers for the continuous-valued multimodal input, whereas the latter will come into play again when the modeled token sequences are to be decoded into an intuitive and vivid image data space.

B. Autoregressive Modeling of Measurement Constituents

Ever since their introduction in 2017, Transformers [9] have seen growing interest and success in both application and research alike. Originally invented with the purpose of advancing machine translation, variations of the original architecture have made their way into various areas like audio generation [74] or bio-informatics to simulate protein folding [75] underlining their remarkable capabilities. More recently, they were also used for image classification [76] and image generation on a per-pixel basis [32] questioning the prevalent role convolutional structures held in this field roughly since 2012 and the famous publication of Alexnet [77], albeit with thus far unheard-of use of computational resources. In the following, transformers will be used to generate consecutive integer sequences and conditionally predict camera image components for given radar tokens.

1) Multiheaded Self-Attention: The unique trademark of any transformer architecture is the incorporated attention mechanism, dynamically modeling relations between all discrete input tokens, irrespective of their relative distance. In contrast to convolutional kernels and their local receptive fields, attention layers lack any inductive biases or preemp-

definite data-based assumptions. Deprived of CNNs key features, transformers instead are given the liberty to form cross-connections between data points during training virtually unconstrained deciding which input to attend to more or less strongly. This allows them to effectively capture global structures and to account for possible correlations among the entire one-dimensional input. Yet, complexity grows quadratically with sequence length \( N \) for reasons of pairwise inner products in the dot product formulation of full attention

\[
A_h = (Q_h K_h^T) / \sqrt{d_h} \in \mathbb{R}^{N \times N}
\]  

in which \( Q_h, K_h \in \mathbb{R}^{N \times d_h} \) represent query and key tensors. These entities are the result of linearly contracting preceding sequence representations with trainable projections \( W_q, W_k \in \mathbb{R}^{D \times d_h} \). This module thus represents a form of soft-attention, since it relies on weighted sums of embedding vectors for its calculation rather than determining hard scores...
between all inputs directly. After scaling with the feature dimension length $d_h$ for an alleged increase in numerical stability, attention matrix $A \in \mathbb{R}^{N \times N}$ gives the inter-token attention scores between all inputs, where each element signifies the pairwise dot-product similarity of the respective key and query vectors. Yet another learnable linear operator $W^e_h \in \mathbb{R}^{D \times d_h}$ is applied to the former sequence features yielding value matrix $V^v_h \in \mathbb{R}^{N \times d_h}$ which is multiplied with the attention map upon softmax normalization

$$H^h = \text{softmax} (A^h) V^v_h \in \mathbb{R}^{N \times d_h}. \quad (27)$$

The described model is reminiscent of information retrieval systems in which a database is queried via its keys for associated values in a data-adaptive importance-weighted manner. In modern transformers, this entire process is replicated and executed separately $H$ times in parallel for this so-called multihread attention supposedly increases model capacity and according to [79] allows it to attend to information from different representation subspace at the same time. To aggregate all heads for subsequent calculations they are concatenated along their feature dimension

$$\text{MSA} = [H_1 | H_2 | \ldots | H_H] W \in \mathbb{R}^{N \times D} \quad (28)$$

before multiplication with a final learnable linear matrix $W \in \mathbb{R}^{D \times H \times d_h}$. Followed by pointwise fully-connected blocks these two layers lay the foundation for nearly every modern transformer architecture. Supplementing both with prefixed layer normalization (LN) for gradient recentering [78] and introducing skip connections around, arguably reduces training time and leads to improved generalization capabilities. To induce a hierarchical structure similar to convolutional networks, numerous of these layers are generally stacked sequentially $L$ times for an increase in depth usually gives superior performance. For a more detailed explanation of this seminal concept and its underlying algorithmic approach, see [79]. Lacking any understanding of spatial relationships within its input sequence, another common characteristic of these autoregressive models is the incorporation of locality information by the addition of positional encoding vectors $e_{\text{pos}} \in \mathbb{R}^{N \times D}$. These typically take either the form of discretized trigonometrical functions or rotation matrices [80]. Lately it has been demonstrated though, that even those vectors can be learned in a data-dependent manner, which further reduces manual interference and thus has been followed here.

2) Multi-Modal Token-Based Likelihood Estimation: Transformer models really shine at sequence modeling, a task in which they are to predict the next part of a certain section, given only the preceding elements to rely on. This so-called autoregressive training with discrete tokens is used in the following, to conditionally forecast camera patches based on supplied radar-frequency data within predefined uncertainty bounds. Concretely, time-synchronized samples of both domains are encoded into their discrete counterparts by means of the pretrained modal-specific encoders, as explained in section III-A with all of their weights frozen. Running in inference mode, these now parameterize true categorical distributions, cf. equation (16), which are sampled from for every latent variable corresponding to $16 \times 16$ partially overlapping patches of the original $256 \times 256$ images as described in section III-A. Both models are now used as priors for the density estimation over sequences outlined in the following. As camera and radar input dimensions are fixed a priori, so is the length $N = h \times w$ of both sequences created line by line using raster order for radar

$$s = [s_{\text{rad}} | s_{\text{cam}}] \in \mathbb{N}^{2N} \quad (31)$$

which serves as input for the autoregressive training process. Given its constant length, no elaborate masking or complex token manipulation needs to be devised. Rather, a simple one-off scheme suffices for the classification setting at hand. After discarding the final element of the above sequence, radar tokens predict their respective successors with the last radar token $s_{N}$ autoregressively projecting the first camera token at position $s_{N+1}$. Progressing in this manner, the last camera token $s_{2N}$ is eventually determined by its immediate predecessor $s_{2N-1}$. Consequently, the target vector is formed by the original integer sequence given in equation (31) after truncating its first element to facilitate autoregressive prediction as illustrated in Figure 16. The model is allowed to make decisions about a current token $s_i$ based only on information derived from preceding positions $s_{i-1}$, which is realized by imposing causal masks on the attention mechanism within every layer. Most often, these are implemented by setting all but the lower triangular matrix in equation (26) to minus infinity prior to softmax normalization. For a certain token under consideration this then yields negligible scores if contracted with the value tensor entries of subsequent elements in the training sequences, and effectively prohibits positions from looking ahead. The training objective in this classification stage is to maximize the log-likelihood of the token permutations given discrete

---

**Fig. 16.** Cross-modal autoregressive sequence modeling with causal attention.
samples of probabilistically compressed synchronous multi-modal input
\[
\arg\max_\psi \mathbb{E}_{x \sim \varphi(x)} \left[ \log p_\psi(s) \right].
\] (32)
This is equivalent to minimizing the cross-entropy between data-conditional priors in the form of both encoder models and estimated discrete distributions over possible categories associated with each dual-domain sample
\[
\mathcal{L}_\psi(x) = -\mathbb{E}_{s \sim \varphi(s \mid x)} \left[ \log p_\psi(s) \right] = \mathbb{H} [\varphi(s \mid x), p_\psi(s)].
\] (33)
Given above token series \(s\) of both modalities, \(p_\psi(s)\) denotes a transformer model emulating the inter-token dependencies
\[
\pi = \text{transformer}_\psi(s_{1:2N-1}) \quad s \sim \varphi(s \mid x).
\] (34)
This sequence model decomposes the joint distribution into factors parameterizing \(2N - 1\) categroicals over possible vocabulary entries \(K\) of each domain according to
\[
\log p_\psi(s_{2:2N}) = \log \prod_{i=2}^{2N} p_\psi(s_i \mid s_{i-1}).
\] (35)
Above equation describes a directed graphical model so that the predicted distribution for any token position is influenced only by the previous section of the input sequence. Masking procedures are applied to the raw logits \(\pi\) to make the first section \(\pi_{0:2} \in \mathbb{R}^{N \times 1 \times 2K}\) only predict radar constituents \(\mathcal{E}_{\text{rad}} \in \mathbb{R}^{K \times D}\) whereas the second part \(\pi_{N+1:2N} \in \mathbb{R}^{N \times 2K}\) including the mass function \(\pi_{N+1} \in \mathbb{R}^{2K}\) associated with the last provided radar entry \(s_N\) is restricted to yield probabilities exclusively over the camera dictionary \(\mathcal{E}_{\text{cam}} \in \mathbb{R}^{K \times D}\). During training, minimizing the cross-entropy in equation (33) thus effectively stimulates the transformer to shift probability mass towards the one-off input token configuration for a given example sequence, improving the prediction accuracy during the course of several runs across the dataset. No sampling takes place along the backpropagation paths, ending just before both inference models which are drawn from merely to provide the network input and ground truth. The objective therefore can be optimized directly via end-to-end training by replacing the expectations with Monte Carlo sampling and adjusting the transformer parameters \(\psi\) with batchwise gradient estimates.

3) Implementation of the Multi-Modal Sequence Model:
In view of the concrete objective of this work, certain modifications and adjustments were necessary to the general transformer framework described in the former section. The algorithm starts by embedding each sequence token separately via a learnable lookup table \(\varphi \in \mathbb{R}^{2N \times D}\) prior to element-wise addition of learnable positional information. The multi-head attention calculations \(h\) in every layer \(\ell\) are succeeded by two adaptable linear operators \(W^1 \in \mathbb{R}^{D \times 2D}, W^2 \in \mathbb{R}^{2D \times D}\) with interleaved Gaussian Error Linear Units (GELU) [81].

Algorithm 1 Autoregressive next-token prediction
Input: Discrete sequences \(x_{\text{rad}} \leftarrow x_{\text{rad}}\) and \(x_{\text{cam}} \leftarrow x_{\text{rad}}\)
Output: Multinomials over successive token sequence
\[
\text{Init: } W_\psi, E_\psi, \mathcal{E}_{\text{pos}} \sim \mathcal{N}(0, 0.02), b_\psi = 0, \gamma = 1, \beta = 0
\]
1: \(s \leftarrow \text{concat}(x_{\text{rad}}, x_{\text{cam}}), s \in \mathbb{R}^{2N-1}
\)
2: \(z_0 \leftarrow [s_1\mathcal{E}_1; \ldots; s_{2N-1}\mathcal{E}_{2N-1}] + \mathcal{E}_{\text{pos}}, z_0 \in \mathbb{R}^{2N-1 \times D}
\)
3: for \(\ell = 1\) to \(L\) do
4: \(z_\ell \leftarrow \text{LN}_{\ell, \gamma}(z_{\ell-1})
\)
5: for \(h = 1\) to \(H\) do
6: \(Q_\ell h \leftarrow z_\ell W^q_{\ell h} + b^q_{\ell h}
\)
7: \(K_\ell h \leftarrow z_\ell W^k_{\ell h} + b^k_{\ell h}
\)
8: \(V_\ell h \leftarrow z_\ell W^v_{\ell h} + b^v_{\ell h}
\)
9: \(A_\ell h \leftarrow \text{masking}(Q_\ell h K^T_{\ell h}/\sqrt{d_h})
\)
10: \(H_\ell h \leftarrow \text{softmax}(A_\ell h)V_\ell h
\)
end for
12: \(z_\ell \leftarrow z_{\ell - 1} + \text{concat}(H_{\ell 1}, H_{\ell 2}, \ldots, H_{\ell H})W_\ell
\)
13: \(z_\ell \leftarrow z_\ell + \text{elu}(\text{LN}_{\ell, \gamma}(z_\ell)W^1_\ell + b^1_\ell)W^2_\ell + b^2_\ell
\)
end for
15: \(\pi_\psi \leftarrow \text{LN}_{\beta, \gamma}(z_\ell)W + b\), \(W \in \mathbb{R}^{D \times 2K}, b \in \mathbb{R}^{2K}
\)
16: return \(\pi_\psi \in \mathbb{R}^{2N-1 \times 2K}\).

Finally, a classification head is attached, consisting of another linear projection \(W \in \mathbb{R}^{D \times 2K}\) followed by a single layer norm, which yields unnormalized probabilities for the intended prediction task. The forward signal flow of a single multi-modal input sequence during the data-fitting process is summarized in Algorithm 1. For improved conditioning of the system matrices, weights of lookup tables and positional embeddings as well as for all linear operators were initialized with values drawn from normal distributions with biases enabled but initially set to zero. All normalization layers had their learnable scale parameters assigned to one without any initial shift. Additionally, dilution, as proposed in [82], was employed quite aggressively at various positions contributing to the overall model regularization. Aside from its concrete application after step 2 and after the softmax operation in step 10 of the algorithm, dropout was also used following the attention and feed-forward blocks in steps 12 and 13 just before adding the skip connections. In combination with input sampling, this measure is to prevent the model from just memorizing token configurations of the training dataset which would entail poor performance on the validation set. Randomly switching off activations during training effectively prunes the network and forces it to continuously find novel features in combination with a varying number of different neurons. The probability of disabling nodes was chosen to be \(p = 0.25\) and slightly but constantly increased with layer index. The latent feature dimension \(D\) was kept constant throughout the entire network and at an integer multiple of the latent dimension of each head \(d_h\) so that their concatenation yields the original feature size again. This is a deliberate decision though, simplifying numerical treatment rather than required by the algorithm itself. Since the relative positions of intensity clusters in rD maps hold immediate meaning and establish
direct correspondences to integral physical quantities like range and velocity (cf. section II), translation and rotation invariance as offered by CNNs are comparatively unfavorable properties. It is expected, however, that the relative ordering of frequency plot constituents given in expression (29) and data-adaptive positional encodings in combination with the attention mechanism will allow the model to attain a basic comprehension about relations between data points as well as their spatial configuration. Yet, conditioning the prediction of camera information on consecutive sections of radio-frequency spectra is challenging due to the inherently low signal-to-noise ratio across vast areas of the frequency plots. It is thus of crucial importance being able to rely on a versatile and expressive discretization scheme of these signal representations, as detailed in section III-A4. Only then will it be possible, to differentiate between the slightest of frequency saliences and discerning even the subtlest of reflections. This, in turn, can only be achieved by providing the compression models of the first stage with enough flexibility for having them assign distinctive vocabulary entries to similar yet different input patches, an issue which was examined extensively in the former sections. Generally, it is hoped that even minor signal parts contained in the radar spectrum might provide useful evidence and, by finding correspondence in camera features, help in improving the distribution predictions of subsequent patches. The same datasets the results of stage one were achieved with are reused in this phase with identical splits into train and validation sets, respectively. Again, no artificial data augmentation was applied for reasons similar to those presented in chapter III-A4. The capacities of both discrete autoencoders and the comparably small dataset used for their parameter estimation imply that sampling from categorical distributions rather than taking the modes of the encoder logits, contrasted against in section III-A5, might add additional regularization and contribute to tackle overfitting. This choice is likely to impose slight amounts of noise onto the targets during likelihood estimation in equation (33) but could prove beneficial, if understood as a form of label smoothing. According to [83] this technique can prevent models from becoming over-confident too early in training. In other words, constructing the multi-modal sequence through sampling provides for soft targets and slightly fuzzy model input in the employed cross-entropy formulation. Also, it pseudo-increases the dataset size by providing added variability of the data distributions. Absolute prerequisite for this strategy are well-adapted compression models which, if sampled from, exhibit sufficient precision so as not to defy the purpose of supplying a ground truth in the first place. Predicting tokens along the entire sequence instead of classifying only the camera-related subpart promotes the models generalization capabilities. In fact, including the error made by forecasting radar tokens in the overall loss formulation keeps the network from focusing too eagerly on the camera token prediction. This auxiliary loss contribution also encourages the exact replication of the preceding RF section and thus has direct influence on the radar conditioning. Its classification error is scaled down by a factor of $\alpha = 1/8$ though to put more emphasis on the camera-related prediction accuracy. To reduce the risk of overfitting further, during training $10\%$ of the input camera tokens are replaced by random integers drawn from the corresponding sample space. This likewise causes the model not to rely on learned internal correlations too strongly, but entices it to acquire more general and robust features instead. All trainings were performed on GeForce RTX 2080 Ti units with $\sim 12$ GB of RAM for compression models with dictionary sizes of $K = 64$, $K = 256$ and $K = 1024$ for both modalities to retain the chance for comparison. A batch size of 16 was chosen and gradients were accumulated over 4 iterations for improved objective estimates with an effective batch size of 64. Decoupled weight decay \cite{84} of $\lambda = 1 \times 10^{-2}$ was used for the Adam solver to adapt the transformer parameters $\psi$ for the classification task while simultaneously constraining their magnitude. The learning rate was set to $3 \times 10^{-5}$ and halved after every 10 validation epochs in which no loss reduction could be observed.

4) Results and Discussion of Multi-Modal Predictions: Table [VI] shows the results of a corresponding study ablating several important parameters of the transformer network structure introduced before. The lowest negative log-likelihood loss (NLL) is reported as central reference metric for the data-fitting progress alongside the epoch on the validation set in which it was recorded. Obviously, models forced to choose among $K = 1024$ possibilities for the prediction of the next token, display higher classification errors than those relying on a dictionary size of $K = 64$ per modality. Then again, a larger selection range may be beneficial for assembling more realistic images, allowing the model to include finer details and differentiate content more clearly as was demonstrated in section III-A5. Additionally, the FID score (cf. equation (24)) was calculated by using the modes of the predicted camera-related distributions over the respective vocabulary to select reconstruction features. These continuous latents were then decoded into image space to fit multivariate Gaussians to the validation dataset as explained in section III-A5. Figure [17] illustrates the models evolvement across epochs on the validation set for the above parameter choices. Inflection points in the classification loss are a sign of overfitting, indicating the point at which a model has reached its maximum generalization potential for a given configuration. Further, the plot shows the average cosine similarity between sampled camera token input and modes of $\alpha = 1/8$

| $K$  | $D$ | $H$ | $L$ | NLL ↓ | Cos-Sim ↑ | FID ↓ | Epoch |
|------|-----|-----|-----|-------|-----------|-------|-------|
| 64   | 256 | 4   | 4   | 1.94  | 0.899     | 161.66| 11    |
|      | 512 | 8   | 8   | 1.92  | 0.902     | 157.71| 4     |
| 256  | 256 | 4   | 4   | 3.05  | 0.923     | 126.38| 37    |
|      | 512 | 8   | 8   | 3.02  | 0.922     | 116.76| 10    |
| 1024 | 256 | 4   | 4   | 5.02  | 0.900     | 125.10| 51    |
|      | 512 | 8   | 8   | 5.00  | 0.894     | 116.04| 11    |
of the predicted PMFs. This quantity serves as a measure of a model’s confidence and expresses its ability to adjust its $N = 256$ camera-related distributions during training. The extent to which the categorical camera latents actually deviate from the mode of their posterior probability mass function (cf. equation (23)) can be quantified by examining the element-wise compliance. This is reported as faithfulness in the given figure for both domains and averaged per epoch over the entire validation set. Even the models with modest dictionary sizes of $K = 64$ sample the largest-probability category only about 3 of 4 times, with minor differences between modalities. This does not necessarily harm the overall density estimation and camera sequence prediction goal since other categories might be almost equally suitable candidates, exhibiting probabilities similar to the modes of the distributions. One possible reason is the acquisition of several nearly identical dictionary features during the compression training in stage one and the advanced interplay between learning vocabulary and adapting generator. In conclusion, the performance of the autoregressive predictor with highest cosine similarity in table VI using $K = 256$ categories as well as the model with $K = 1024$ per modality and lowest FID score appear most promising and will be used in the final evaluation part. Figure 31 and Figure 33 in the appendix highlight the inter-sequence attention span for one exemplary sample if passed through both trained transformers. The illustration allows to qualitatively examine in which head of which layer camera tokens paid particular interest to radar information. Showing only the lower-left submatrix gives clear insights into the formed cross-modal connections within the network. The original input and their approximate discretization boundaries are indicated alongside the corresponding attention maps in Figure 30 and Figure 32 for visual reference.

C. Conditional Synthesis of Camera Symbols

Having successfully adapted the transformer weights and biases to the training sequences, the ultimate proof of concept yet remains. Supplied with nothing but radio frequencies, is the model able to construct a high-fidelity view of the sensed environment and capture the essential details and important aspects of the surroundings? If so, this would open up unprecedented possibilities for the control of autonomous systems in disadvantageous circumstances and significantly enhance the safety of related applications. To investigate the stochastic composition of radar-conditioned camera images, rD maps of the validation dataset are tokenized as given by equation (29) and serve as input to the autoregressive predictor without any camera information to rely on. As per defined procedure described in section III-B2 and according to the incorporated causal attention, the networks very last output yields a distribution over all possible camera constituents. The associated PMF is conditioned exclusively on microwave-sensed information and discrete sampling results in the first camera token, corresponding to the content of the upper left image region. This autoregressive decision process is influenced by all radar latents fully attended to in all transformer layers. After appending the found camera index to the initial RF part, the sequence is input into the transformer again so that the next camera token is depending not only on radar features but also the formerly predicted camera component and its high-dimensional representation within the model. This iterative process is repeated, obtaining one symbol at a time, until all 256 camera indices have been determined. Drawing on an ever-growing amount of prior information, makes the model’s decisions increasingly confident but also strongly dependent on the quality of previous predictions. In fact, having by chance, sampled a suboptimal initial camera token can possibly cause the entire subsequent synthesis to deteriorate. This is an important consequence of choosing

$$p_{\psi}(s_i) = \prod_{i} p_{\psi}(s_i | s_{1:i-1})$$

Fig. 18. Autoregressive prediction of camera content based on discretized radar information and successively generated camera components.

...
intuition, the described generation procedure is depicted in Figure 18 for a single sample stream and some camera tokens already predicted. Upon sequence completion, the detached camera section selects the respective camera-specific dictionary entries before those are reshaped and eventually decoded by the camera generator into the desired view. Given its stochastic nature, the results accomplished by the presented method are better investigated by visual inspection rather than by quantitative measures. Figure 19 exemplarily shows two randomly inferred probabilistic views of the environment based on prior RF information. For reference, the actual camera image is displayed as well as the straight-forward reconstructions via categorical samples of both domains as introduced in section III-A5 for the discretization task. The replicated rD map provides insight into the radar conditioning the model can build upon for predicting the view. The camera reconstruction should serve as an upper bound for the visual quality, achievable by the algorithm. Finally, the illustration also displays the frequency plot recovery based on the modes of the autoregressive forecasting of the radar subsequence. Even though, these have no influence on the actual synthesis as only the original discretized RF sequence is used for conditioning, this image allows to obtain a notion of the models inner workings resulting in the final context prediction. The model generally succeeds in reproducing the global structure of the surroundings and for the most part manages to compile a realistic rendering of its central components. Occasionally, regions show severe artifacts or distortions of objects within the scene. Backgrounds are usually reflected accurately and sharp, presumably due to its limited variation within the dataset. Also, the first camera symbol, if sampled carefully based on synchronous RF input, seems to be a strong informant with major influence on the following visual assembly, determining the overall composition quality. Additional results substantiating the validity of the approach can be found in Figure 34 to Figure 38 in the appendix alongside the attempt to justify the specific conclusions made by the models in both visual and written form. Additionally, Figure 39 to Figure 44 highlight the actual prediction process and explain possible links between RF conditioning and generated outcome. It is important to note that the network is not provided any temporal context which would significantly simplify the forecasting task and make the prediction more accurate. As no resampling is applied to correct for vastly misclassified first camera tokens, the importance of drawing high-quality samples cannot be overstated. Introducing a temperature parameter into the softmax normalization of the raw transformer logits akin to equation (18) and truncating the tails of the PMF by top-k selection, enables so-called nucleus sampling of the camera tokens. More precisely, shrinking the sample space to only a few categories \( \hat{K} \ll K \) comprising the bulk of the probability mass increases both the sample quality and reliability by preventing low-probability outcomes. Then, for larger temperatures \( \tau > 1 \) the truncated densities become more uniform, which promotes sample diversity. Smaller values \( \tau < 1 \) on the other hand, further enhance large Fig. 19. Range-Doppler maps (green) contain information unaffected by lighting conditions, shadow casting or occlusion phenomena. The probabilistic generations of the camera view (red) can therefore rely on a robust and stable perceptual prior to not miss out on vital scene elements. For visual reference, the ground truth camera image (blue) as well as the stochastic reconstructions of both discretized domains (yellow) are given. The autoregressively predicted radar reconstruction (purple) allows a visual inspection of the causal conditioning within the transformer network. The synthesized views convey clear impressions of the environment, even if the number of objects or their exact position and orientation is slightly off at times.
probabilities and thus strengthen sample coherence. This claim can be investigated by consulting Figure 45 to Figure 48 in the appendix. Additional illustrative material and videos showcasing video sequences of various reconstructed outdoor scenes can be found at cditzel.github.io/GenRadar. Clearly, the models are capable of synthesizing intuitive camera views albeit with varying degree of realism and credibility to them. Often times it is difficult to explain why one particular image has a more natural look and feel to it than another. At other times, the defects are more evident or the model is just completely off with its predictions. Unsurprisingly, typical failure modes are horizontally-flipped generations with respect to the camera ground truth. As mentioned in section I-A, the rD maps lack any azimuthal information which would better help the network to distinguish left from right. The important aspect though, as mentioned in the beginning of this paper, is the recovery of essential information and the visual identification of central elements for the decision-making of autonomous systems. The designed method regularly succeeds in reflecting on the integral objects present in a scene and is able to plausibly reconstruct most crucial entities located in the sensors vicinity. For safety-critical systems, the accurate representation of human anatomy or the exact topological order of potentially dangerous obstacles is often less relevant than those objects mere detection and robust localization. At times, the models compose completely new and artificial scenes can be found at cditzel.github.io/GenRadar. Clearly, the models are capable of synthesizing intuitive camera views. Often times it is difficult to explain why one particular image has a more natural look and feel to it than another. At other times, the defects are more evident or the model is just completely off with its predictions. Unsurprisingly, typical failure modes are horizontally-flipped generations with respect to the camera ground truth. As mentioned in section I-A, the rD maps lack any azimuthal information which would better help the network to distinguish left from right. The important aspect though, as mentioned in the beginning of this paper, is the recovery of essential information and the visual identification of central elements for the decision-making of autonomous systems. The designed method regularly succeeds in reflecting on the integral objects present in a scene and is able to plausibly reconstruct most crucial entities located in the sensors vicinity. For safety-critical systems, the accurate representation of human anatomy or the exact topological order of potentially dangerous obstacles is often less relevant than those objects mere detection and robust localization. At times, the models compose completely new and artificial environments not included in the training data but which it obviously deemed most corresponding to the supplied rD frequency information. This gives a hint towards the possible capabilities and the true potential of these generative models in general. Some of those rather abstract defective attempts are illustrated in Figure 49 in the appendix.

IV. CONCLUSION AND LIMITATIONS

Autonomous systems need to be able to rely on a fail-safe and instructive environment perception, independent of their current surrounding conditions. Camera images are prone to all sorts of weather-induced failings and therefore have to be supplemented with complementary robust measuring principles like radar to ensure a stable inflow of information. Yet, range-Doppler frequencies usually lack the intuitive representation cameras provide. It is thus worth attempting to combine the advantages of sensors and aim for an enhanced visual impression of their proximity. As a possible solution, this paper demonstrated the design and applicability of a self-learning model, capable of generating insightful camera views conditioned on millimeter-wave sensing. Circumventing the need for explicit data-annotations, the system combines the strengths of convolutional and transformer architectures to exploit a maximum of multi-modal information and to make predictions about the sensors vicinity. First, imposing a stochastic bottleneck onto the convolutional input restoration task led to the effective and discrete compression of the high-dimensional measurements in both domains. Second, the resulting memory-efficient symbol representation was assessed by an autoregressive sequence model, establishing cross-modal dependencies through its attention mechanism. Multiple qualitative and quantitative results proved, that the system eventually learns the multi-sensory composition of captured surroundings. This ultimately allows for the visual reconstruction of environments by predicting radar-conditioned distributions over camera components. Validity and expressiveness of the results as well as the models generalization abilities relate directly to the amount and diversity of the available data. Consequently, in order to create even more generic and realistic predictions, not only the datasets size but also the network’s complexity would need to be enlarged by orders of magnitude. Additionally, at the expense of even larger data volumes, radar-based angle estimations should be employed to exclude the systemic lateral position error from the predictions. Nonetheless, has this feasibility study revealed the future potential and far-reaching possibilities of self-supervised systems if applied to low-level multi-modal sensor data. Particular value is attributed to the complementary nature of the employed sensor types, providing unique and characteristic features for the correspondence learning task in the second stage. Although the effectiveness of convolutional operations for natural images is indisputable, the same might not hold true for range-Doppler maps. In fact, it is arguable if the employed frequency plots are even the most suitable representation for the purpose of neural network processing. Perhaps the data could be siphoned even closer to the sensor, intercepting the IF-signal immediately after the mixing process. Also, the probabilistic discretization of the rD maps marks the confluence point of the entire RF spectrum. Performed carelessly, this compression discards potentially important information, entailing major problems for the following cross-modal correspondence learning and the coherent combination of sensor constituents. It would therefore be interesting to search for alternative ways of integrating the radar information into the multi-modal fusion process.

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Fig. 20. Two-dimensional Fourier decomposition of a differential frequency signal over multiple chirps. Ramp-synchronous sampling across frequency excursions allows for the identification of phase shifts between chirps. The derived Doppler information is used to discriminate objects at equal distance to the sensor through the slightest of differences in relative velocity. Radial range and relative velocity constitute powerful discriminative features to complement the strengths of camera sensors.
Fig. 21. Performance development of the stochastic discretization models with varying dictionary sizes on the validation dataset after every training epoch. The first three plots show similar but slightly different decreases in the reconstruction error, depending on the respective sampling method as explained in section III-A4. The KL-term stabilizes during the training progress and eventually settles for an equilibrium which trades uniformity in vocabulary use for more customized latent spaces. The contradiction between maximum entropy configuration excited by the uniform prior and fulfillment of the reconstruction objective through an increase in divergence is clearly recognizable.
Fig. 22. Camera and radar input (top row) and probabilistic reconstructions for dictionary sizes of $K = 64$ (left) and $K = 1024$ (right). The second row displays results achieved by mode/argmax selection of the latent categories. The third row highlights the restoration of using concrete samples in the stochastic bottleneck and the fourth row shows results obtained by categorically sampling the domain constituents. The bottom row shows the frequency of these chosen categorical entries for the given input. With a larger vocabulary size, the model is able to retain more details by assigning separate categories to infrequent image content. The reconstruction quality based on categorical latent samples is comparable to the restoration achieved by the other two sampling methods, which visually proves the efficacy of the stochastic discretization approach.
Fig. 23. Camera and radar input (top row) and probabilistic reconstructions for dictionary sizes of $K = 64$ (left) and $K = 1024$ (right). With a larger vocabulary size, the model is able to retain more details by assigning separate categories to infrequent image content. This becomes particularly apparent by looking at the pedestrians rendering. The reconstruction quality based on categorical latent samples is comparable to the restoration achieved by the other two sampling methods.
Fig. 24. Camera and radar input (top row) and probabilistic reconstructions for dictionary sizes of $K = 64$ (left) and $K = 1024$ (right). With a larger vocabulary size, the model is able to retain more details by assigning separate categories to infrequent image content. As a case in point, the lost tyre is barely recovered by the model with $K = 64$ but is clearly retained by the model with $K = 1024$. Radar models with larger dictionaries are able to resolve the noise pattern within rD plots with larger accuracy.
Fig. 25. In this particular example, it is difficult to recognize the superiority of the camera model having a vocabulary size of $K = 1024$ over the reconstruction capabilities of the model with $K = 64$. The training data probably does not feature enough samples akin to the above to allow the network to reconstruct the scene in sufficient quality. The histogram plot speaks for a rather uniform dictionary utilization in both cases so that the model assigned separate categories to similar but distinct image patches.
Fig. 26. Selection of fail cases observed on the validation set during the probabilistic reconstruction training in stage one. The reasons for erroneous restorations are manifold, ranging from unfavorable initial weight constellations to imbalanced weightings between reconstruction and entropy loss terms in the VLB. The images clearly show the tiling subdivision of the input due to their regular discretization in squared patches. **Left, center and right image:** The model wrongly assembles the image by means of dictionary entries tuned to different camera samples. **Second to the left image:** The reconstruction exhibits severe artifacts and over-colorizes the output. **Second to the right image:** The model fails to infer color channel and instead shows checkerboard patterns, vastly neglecting the coverage of high-frequency details and fine-grained structures.

Fig. 27. Typical failure modes of both modalities observed during the training process in stage one. The models fail to restore both local and global features and neglect the vast majority of image contents. **Camera images:** The camera data is recovered beyond recognition for overly exaggerated entropy weights or too rapid temperature declines. **Left image:** The numerical procedure did not properly converge for an initial Gumbel-Softmax temperature larger than one. **Second to the right image:** The regularization term in the loss function was given too much influence forcing the model to uniformly use almost all dictionary entries which hinders data restoration.
Fig. 28. Successively choosing identical indices for all latent variables and decoding the corresponding feature vector of the dictionary with $K = 256$ back into image space provides insights into the model’s diversity, adopted during training. The individual patches themselves are rarely homogeneous due to spatially overlapping upsampling and specific boundary treatments within the convolutional decoders. Visual redundancies between patches could hint towards potential redundancies in the acquired vocabulary and might justify dimensionality reductions of the model.

Fig. 29. Illustration of the latent code space utilization over the entire validation dataset. For the illustration, the modes of the 256 encoder-induced probability mass functions are recorded and accumulated across all input samples. This allows for yet another visual impression regarding the efficacy of the probabilistic discretization procedure and the desired uniform exploitation of the designed latent space. Random distribution patterns speak for a versatile and expressive use of the provided vocabulary. A smaller number of pronounced vertical lines on the contrary means a regular selection of that particular category by a large number of latent variables.
Fig. 30. Approximate discretization regions each token represents upon stochastic decomposition. In reality, subsampling in combination with zero-padding of the boundaries entails slight overlapping between the individual patches. The larger the downsampling (a factor of 16 was chosen in this work), the smaller the memory requirements within the transformer model. Yet, for stronger compression ratios, the discretization grid would become less refined and individual integers had to represent larger amounts of continuous sensor data, generally compromising information preservation.

Fig. 31. Attention span for the transformer with 4 layers and 4 heads and the discretized multi-modal input shown above, compressed by models with dictionary sizes of $K = 256$. Only the lower-left submatrix (cross-modal attention part) is shown for improved visualization. Local maxima in every plot denote camera tokens attending to radar information. Often, camera symbols reacting most actively to the radio-frequency conditioning are located in the upper half of the subimages. This is to be expected, as the first few camera constituents are predicted almost exclusively, depending on the radar spectrum, particularly in the first few layers. For subsequent layers as the information is transmitted deeper into the network, the attention span is significantly broadened. Best viewed in color and zoom on a computer.
Fig. 32. Approximate discretization regions each token represents upon stochastic decomposition. In reality, subsampling in combination with zero-padding of the boundaries entails slight overlapping between the individual patches. The larger the downsampling (a factor of 16 was chosen in this work), the smaller the memory requirements within the transformer model. Yet, for stronger compression ratios, the discretization grid would become less refined and individual integers had to represent larger amounts of continuous sensor data, generally compromising information preservation.

Fig. 33. Attention span for the transformer with 8 layers and 8 heads and the discretized multi-modal input shown above, compressed by models with dictionary sizes of $K = 1024$. Only the lower-left submatrix (cross-modal attention part) is shown for improved visualization. Local maxima in every plot denote camera tokens attending to radar information. Often, camera symbols reacting most actively to the radio-frequency conditioning are located in the upper half of the subimages. This is to be expected, as the first few camera constituents are predicted almost exclusively, depending on the radar spectrum, particularly in the first few layers. For subsequent layers as the information is transmitted deeper into the network, the attention span is significantly broadened. Best viewed in color and zoom on a computer.
Fig. 34. Five random samples taken from the validation dataset and the probabilistic camera view reconstruction with top-1/mode sampling of models with $K = 256$ based on the depicted RF information (green). The same color coding introduced in Figure 19 applies. The transformer model is capable to include most of the essential scene elements in the reconstructions (red) albeit with some creative freedom concerning their position and number. A general problem is the orientation of entities like cars and pedestrians. Only the camera sensor provides azimuthal information so that predictions with respect to the lateral positioning of objects are naturally less accurate than estimating their radial distance.
Fig. 35. Surprisingly, at times, the top-1 predicted environment perception (red) for the models with $K = 256$ surpasses the stochastic reconstruction of the discretized camera image (yellow) in terms of visual quality and contour sharpness, as for the dark car in the left example. Again, the model confuses left and right and therefore mixes up the direction of the car driving in the roundabout. Sometimes, it only manages to include rough sketches of what seems to be pedestrians or synthesizes artificial car shapes. The same color coding introduced in Figure 19 applies.
Fig. 36. For highly dynamic scenarios, the model with $K = 256$ can become distracted so that the radar-based conditioning is impaired and spread out across most Doppler cells (purple). As a consequence, the network assumes the existence of fast extended objects and, for top-1 sampling, integrates suitable elements into the scene which it saw during cross-modal training (second and fifth example). The center illustration shows a typical case in which the prediction qualitatively outranks the visual upper bound (yellow), i.e. the immediate reconstruction of the discretized input, although the cars distance is slightly off. The same color coding introduced in Figure 19 applies.
Fig. 37. The transformer model relying on compression models with $K = 1024$ and top-1 sampling are likewise able to infer the general topological ordering of diverse outdoor scenes but with enhanced level of detail (red). However, they too suffer from lateral position insecurity and generate objects with azimuthal offset or reversed orientation into the environment. The inferred entities are sometimes just indistinct shapes in the darkness but still convey vital information about the potential existence of dangerous objects in front of the sensor. The same color coding introduced in Figure 19 applies.
Fig. 38. The model with $K = 1024$ and top-1 sampling is able to infer the relative distance between obstacles and sensor with high precision but occasionally misses out on individual subjects entirely. The inclusion of even partially occluded pedestrians in the far background (third and fifth example) underlines the significance of using a complementary multi-modal sensor setup and supports the arguments stated in the introduction about retaining as much information as possible. The same color coding introduced in Figure 19 applies.
Fig. 39. **Prediction process, RF conditioning** and **camera GT:** The parked car reflects strongly on the vertical rD line, and the model includes it in its generated view. Multiple additional scatterings at various distances causes the network to become insecure about the precise number of dynamic reflectors in the scene. Both compression models use $K = 256$.

Fig. 40. **Prediction process, RF conditioning** and **camera GT:** The model synthesizes two abstract VRU representations in the foreground but misses the two persons in the background. The white parked car shows as a strong reflection on the vertical center line of the rD plot and is included in the generated view. The black car is beyond the maximum range of the radar so that the algorithms fails to establish a cross-modal correspondence, precluding it from the final image. Both compression models use $K = 256$.

Fig. 41. **Prediction process, RF conditioning** and **camera GT:** Dynamic objects like the two VRU and the moving vehicle can be discriminated via their relative radial velocities in the rD map. With no angle information included in the signal though, the model is unsure about their lateral position and general orientation. It generates trees and about one and a half persons at rather random positions. Both compression models use $K = 256$. 
Fig. 42. **Prediction process, RF conditioning and camera GT:** This highly dynamic scene is well resolved via unique Doppler frequencies and allows the model to almost accurately predict the number of VRU in the scene through abstract creations. Their distance to the sensor is featured almost exactly and allows for an immediate assessment of the environment. Both compression models use $K = 1024$.

Fig. 43. **Prediction process, RF conditioning and camera GT:** Both vehicles are clearly recognizable through their rD signatures by revealing multiple reflection centers and are therefore included in the created camera view with large probability, albeit with deviant angular precision. Both compression models use $K = 1024$.

Fig. 44. **Prediction process, RF conditioning and camera GT:** Being out of the cameras horizontal field of view, the retracting vehicle is originally not captured by the camera sensor (lower-right image). Aside from multiple VRU-caused echoes, the networks attention is drawn to the car’s reflection in the radar modality (right half of the rD map). It therefore correctly includes a corresponding car representation in the camera view. Both compression models use $K = 1024$. 


Table 45. Nucleus and top-k inference with a limited number of categories $\hat{K} = 25$ to sample camera constituents from. The temporal context underlines the differences in synthesis quality when the sample temperature varies. Unconstrained category selection over the entire camera sample space $K = 256$ as well as top-1 sampling with $\hat{K} = 1$ serve as basic visual references. Most strikingly is the change in inferred car color and car positions for different temperatures highlighting this parameter's influence. For too large temperatures, the model still predicts some coarse tendencies correctly but generally fails to achieve a valid scene reproduction. The same color coding introduced in Figure 49 applies.
Fig. 46. Nucleus and top-k inference with a limited number of categories $\hat{K} = 25$ to sample camera constituents from. The temporal context underlines the differences in synthesis quality when the sample temperature varies. Unconstrained category selection over the entire camera sample space $K = 256$ as well as top-1 sampling with $\hat{K} = 1$ serve as basic visual references. This challenging scenario at dawn with glaring lights is sufficiently recovered, but the model occasionally senses more VRU than actually present, places the car in the center of the road or erroneously turns on its rear lights. These errors are understandable having their origin in the absence of cross-modal correspondence and rarely compromise the validity of the perception in terms of risk assessment. The same color coding introduced in Figure 19 applies.
Fig. 47. Nucleus and top-k inference with a limited number of categories \( \bar{K} = 25 \) to sample camera constituents from. The temporal context underlines the differences in synthesis quality when the sample temperature varies. Unconstrained category selection over the entire camera sample space \( K = 256 \) as well as top-1 sampling with \( \bar{K} = 1 \) serve as basic visual references. Multiple similar reflections by static objects like poles, tires and parked cars as well as micro-Doppler information of pedestrians make this scene challenging. The model is able to recapitulate only some of its complex details, but regularly confuses the number and position of the VRU. Missing out on individuals is the worst-case scenario for autonomous systems whereas generating VRU in the proximity of the sensor when there are actually none is less problematic. The same color coding introduced in Figure 19 applies.
Fig. 48. Nucleus and top-k inference with a limited number of categories $\hat{K} = 25$ to sample camera constituents from. The temporal context underlines the differences in synthesis quality when the sample temperature varies. Unconstrained category selection over the entire camera sample space $K = 256$ as well as top-1 sampling with $\hat{K} = 1$ serve as basic visual references. The unique Doppler signature of the passing tram is used to establish cross-modal correspondence so that the model correctly depicts train-resembling instances in the synthesized scene. The standing car only shows in the range section of the frequency plot without any relative velocity to the sensor and is therefore easier to miss by the models attention. The same color coding introduced in Figure 19 applies.
Fig. 49. Typical fail cases that occur during the probabilistic inference phase (red) below the actual camera ground truth (blue). The reasons for the various misconceptions and complex errors are obscure and not always immediately comprehensible. Still, it is instructive to take a closer look at the many deceptive examples to get a better understanding of the models assumptions and trains of thought.