

Reliable measurements for safe rescue operations after building collapses (ZeMeRGe)

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Abstract

This contribution presents an overview of the ZeMeRGe project, which aims to develop reliable sensor systems for search-and-rescue operations in disaster scenarios. In particular, a radar-based system for contactless vital sign detection is investigated, enabling the detection of respiration in survivors trapped under debris using an unmanned aerial vehicle (UAV).

While the feasibility of radar-based vital sign detection has been demonstrated in previous work, its practical deployment requires a systematic understanding of measurement uncertainty. This paper introduces the underlying measurement principles and discusses the main factors influencing detection reliability, including physiological variability, UAV motion, environmental effects such as debris composition, and radar system design parameters.

Different radar approaches, including stepped-frequency continuous-wave (SFCW) and frequency-comb continuous-wave (FCCW) systems, are presented and compared in the context of UAV-based operation. In addition, simulation methods based on finite-difference time-domain techniques are introduced as a tool for controlled uncertainty analysis.

Experimental results obtained under laboratory and field conditions illustrate the impact of target orientation and platform motion on signal quality and detectability. The presented results provide a foundation for future quantitative uncertainty budgets and contribute to the development of robust and trustworthy radar-based systems for supporting first responders.

Keywords: radar, vital sign detection, measurement uncertainty, unmanned aerial vehicles

Introduction

In disaster scenarios such as earthquakes or gas explosions, emergency personnel must rapidly assess both environmental hazards and the presence of survivors. Currently, rescue dogs are widely used for victim detection. However, their deployment is limited in duration due to fatigue, and they cannot be used in hazardous environments, such as areas with potential gas leaks.

These limitations motivate the development of complementary technological solutions. Within the ZeMeRGe project, a radar-based approach for contactless vital sign detection for deployment on unmanned aerial vehicles (UAVs) is investigated at the Department of Microsystems Engineering (IMTEK). This so-called bioradar exploits the Doppler modulation caused by periodic thoracic motion to detect human respiration, as illustrated in Fig. 1.

While previous studies have demonstrated the feasibility of radar-based vital sign detection, it has become evident that detection performance strongly depends on environmental and

system-related factors. These include debris composition, the orientation of the survivor, UAV motion, and radar system parameters. As a result, first responders consistently raise a critical question: How reliable are the measurements?

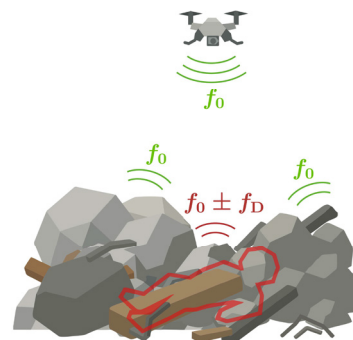


Fig. 1: Radar-based vital sign detection from a UAV. While clutter in the environment does not modulate the radar echo, thoracic movement introduces a Doppler shift.

To address this, the ZeMeRGe project aims to systematically quantify the measurement uncertainty of both the bioradar and a complementary gas sensing system, following the GUM (Guide to the Expression of uncertainty in measurement) methodology [1]. For the radar system, this requires understanding how physical, environmental, and algorithmic factors influence the detectability of respiration signals.

Bioradar measurement principle

Radar-based vital sign detection relies on the fact that human respiration induces small, quasi-periodic movements of the chest. These movements modulate the reflected electromagnetic wave and can be detected remotely.

In a bioradar system, electromagnetic waves in the low GHz range are transmitted towards a target area. The waves propagate through the environment, including debris, and are partially reflected by objects such as the human body. The periodic displacement of the chest induces a Doppler shift in the backscattered signal, thereby enabling the extraction of vital-sign information. The received signal therefore contains information about motion-induced changes in phase and amplitude, as illustrated in Fig. 2. This principle is well-known in medical monitoring of vital signs [2] as well as for search-and-rescue (SAR) missions [3], as is the case for this project. While radar-based vital sign detection, especially in the medical context, is an active research field, little is known about measurement uncertainty in SAR applications, especially on UAVs.

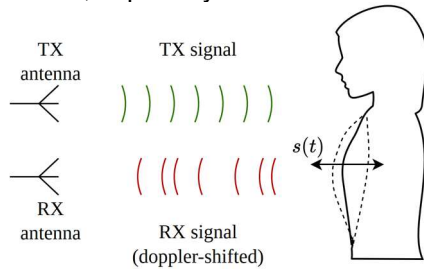


Fig. 2: Working principle of the bioradar. The echo signal is modulated in both frequency/phase and amplitude by the chest movement.

The thoracic motion can be approximated as a quasi-periodic displacement

$$s(t) = s_{pp} \sin(2\pi f_{resp} t) \quad (1)$$

with the breathing frequency f_{resp} and the peak-to-peak chest displacement s_{pp} . The assumption of quasi-periodicity is justified by

the relatively stable respiration rate over short observation intervals.

For adults at rest, the respiration rate typically lies between 12 and 20 breaths per minute (0.2 to 0.33 Hz), although significant variability can occur in practice [4]. This frequency range is important for system design, as it enables the discrimination of respiration from other motion sources, such as environmental clutter or mechanical vibrations. In addition to phase modulation (Doppler effect), respiration also alters the radar cross-section of the chest due to volumetric changes. Both effects can be exploited to estimate the breathing frequency.

Radar signal chain

To better understand how this information is extracted, it is useful to consider the underlying signal model.

The transmitted radar signal $r_{TX}(t)$ propagates through the environment and is reflected by a target at distance R . The received signal can be approximated as

$$r_{RX}(t) = \alpha \cdot r_{TX}(t - \tau) + n(t), \quad (2)$$

where α represents attenuation due to propagation and reflection, τ is the round-trip delay, and $n(t)$ denotes noise and interference. For a breathing human target, the radar distance $R(t)$ determining the round-trip delay is time-dependent with

$$R(t) = R_0 + s(t), \quad (3)$$

where $s(t)$ describes the respiration-induced chest displacement as described in Eq. (1) and R_0 is a time-independent radar distance component. This results in a time-varying phase modulation of the received signal $r_{RX}(t)$. For a single frequency component with wavelength λ , the phase φ is given by

$$\varphi = \frac{4\pi}{\lambda} s(t). \quad (4)$$

Thus, even small chest movements on the order of millimetres lead to measurable phase changes in the radar signal, which form the basis for respiration detection. Based on this signal model, the choice of radar waveform determines how spatial (range) and temporal (motion) information can be extracted from the received signal.

Radar types in CW vital sign detection

In its simplest form, a continuous-wave (CW) radar operating at a single frequency, as used in simple motion sensors in smart home applications, is sufficient to detect motion

through Doppler modulation. However, such systems cannot provide any information about the distance of the detected motion. This limitation is critical in search-and-rescue scenarios, where multiple motion sources may be present. Without spatial resolution, it is impossible to distinguish between relevant signals (e.g., a buried survivor) and irrelevant ones (e.g., moving vegetation), if they happen to exhibit similar Doppler shift frequencies. Fundamentally, the range resolution ΔR of a radar is given by

$$\Delta R = \frac{c}{2 \cdot BW} \quad (5)$$

with the speed of light c and the bandwidth of the excitation signal BW . This range resolution relation follows from the fact that radar distinguishes targets by their propagation delay. The smallest resolvable delay difference $\Delta\tau$ is inversely proportional to the signal bandwidth BW by

$$\Delta\tau \approx \frac{1}{BW}. \quad (6)$$

Since radar measures round-trip delay, range R and delay are related by

$$R = \frac{c\tau}{2}. \quad (7)$$

Hence, the corresponding range resolution takes the form of Eq. (5). A larger bandwidth therefore improves the ability to separate targets in distance. Intuitively, a larger bandwidth enables finer discrimination between different propagation delays and thus between different target distances.

To achieve this required bandwidth, different radar concepts have been developed, each with specific advantages and trade-offs in terms of complexity, measurement speed, and robustness.

One widely used approach is frequency-modulated continuous-wave (FMCW) radar. In FMCW systems, the transmit frequency is continuously swept over time. Due to the propagation delay, the received signal exhibits a frequency offset relative to the transmitted signal, which is proportional to the target distance.

An alternative approach is stepped-frequency continuous-wave (SFCW) radar. Here, the required bandwidth is synthesised by frequency hopping, i.e., sequentially transmitting discrete frequency tones. The phase differences across these frequencies are then combined to reconstruct a range profile using Fourier-based processing. While SFCW offers high flexibility

and accurate range estimation, this approach is inherently time-consuming due to the sequential frequency sweep. After each frequency hop, the synthesiser requires a finite settling time before a phase-stable measurement can be acquired. Since this stabilisation delay occurs at every frequency step, the total sweep duration increases with the number of sampled frequencies.

To circumvent this issue, one approach currently being investigated in the ZeMeRGe project employs a frequency-comb continuous-wave (FCCW) radar. In this system, multiple frequency components are transmitted simultaneously. This enables instantaneous wideband operation, significantly faster acquisition, and reduced synchronization requirements compared to FMCW and SFCW. These properties make FCCW particularly attractive for UAV-based bioradar applications, where measurement time, system flexibility, and robustness against motion are critical.

In practical implementations, the range information obtained from both SFCW and FCCW is discretized into so-called range bins, where each bin corresponds to a specific distance interval from the radar. By transforming the multi-frequency signal into the spatial domain, the received signal can be decomposed into multiple distance-dependent components. Each range bin can then be analysed individually in the time domain, allowing the separation of relevant signals, such as human respiration, from other motion sources located at different distances. The spatial extent of each range bin is determined by the range resolution ΔR given by Eq. (5). For the FCCW radar system with a bandwidth of approximately 60 MHz, this results in a range bin width of approximately $\Delta R \approx 2.5$ m.

After range separation, each range bin provides a time-dependent signal corresponding to a specific spatial region. These signals are typically analysed in the slow-time domain to extract periodic components associated with respiration. In this contribution, spectral methods such as the fast Fourier transform (FFT) and time–frequency methods such as the continuous wavelet transform (CWT) are used to estimate the respiration frequency. These methods allow robust extraction of periodic components even in the presence of noise and non-stationary effects.

Sources of measurement uncertainty

The measurement uncertainty of bioradar-based vital sign detection is influenced by multiple factors, which can be grouped into four main categories.

First, the respiration rate is not constant. Its frequency and amplitude are variable over time. Additionally, the orientation of the body relative to the radar significantly affects the observable motion component.

When operating from a hovering UAV, small translations or rotations during the measurement alter the distance between radar and target, creating phase offsets indistinguishable from human motion unless corrected with additional hardware.

Material, geometry and properties of the debris site are highly unpredictable in practical scenarios and influence the measurement results. For materials with high electromagnetic transparency, e.g., wood, the attenuation or power loss due to the reflections of the radar waves are significantly weaker compared to materials with metal components, e.g., reinforced concrete. Any claim about the measurement uncertainty is thus only valid for a certain material composition, and for different compositions, the assessed uncertainties will differ.

Finally, many design choices of the radar hardware and processing affect the final measurement uncertainty. For example, the choice of operating frequency in the low GHz range represents a trade-off between penetration capability and system size. Lower frequencies exhibit reduced attenuation in common building materials and therefore improve the ability to detect signals through debris. However, the wavelength λ increases with decreasing frequency, requiring larger antennas, which is a critical constraint for UAV-based systems. In practice, frequencies in the range of 1 to 3 GHz provide a suitable compromise between penetration depth and system integration. Transmit power affects the signal-to-noise ratio and thus the minimum detectable motion, but at the same time, the available transmit power is limited both by the hardware and by regulatory and medical limits for maximum radiation exposure. The choice of signal processing algorithms influences frequency resolution via the time-frequency trade-off, as well as by their efficiency at extracting the respiratory rate. Additionally, measurement duration directly influences the achievable spectral precision.

A key parameter influencing all these contributions is the signal-to-noise ratio (SNR). Due to path loss, material attenuation, and imperfect reflections, the received signal amplitude decreases significantly with increasing distance and obstruction. At the same time, system noise and environmental clutter remain present, reducing the effective SNR. As a result, respiration-induced

modulations may become indistinguishable from noise, directly impacting both detection reliability and frequency estimation accuracy.

Previous research at the Department of Microsystems Engineering

In the preceding FOUNT2 [5] and SORTIE projects [6], the foundation for the current bioradar system was developed. In [7], a frequency-comb continuous-wave radar (FCCW) is introduced as a bioradar, enabling rapid software-defined radio (SDR) prototyping since no transmit-receive synchronization is required. In [8], this bioradar platform was extended with the use of prominent features in the FFT and CWT spectra of the radar signal. A linear support-vector machine was trained on these features to automatically detect survivors. However, this performance does not directly translate to real deployments, where a quantitative evaluation of the system is still to be conducted. Hence, ZeMeRGe shifts the focus from classification accuracy to measurement uncertainty quantification.

Simulation approaches

To enable systematic uncertainty analysis, simulation-based approaches are employed, allowing controlled variation of environmental and system parameters. In order to efficiently simulate the system, different approaches are possible. In [9], a computationally efficient framework of the vital sign detection radar with the finite-difference time-domain (FDTD) method for sparse frequency excitations is presented, building on the simulation of a beat period of the radar signal instead of a full period. Instead of simulating continuous motion, multiple static configurations corresponding to different chest positions are computed and combined to reconstruct the temporal signal. By using the FDTD method, it is possible to incorporate complex materials, e.g., by using Debye dispersion. However, it inherently neglects certain real-world effects, such as noise, and therefore provides insight into fundamental limits rather than complete system performance.

In addition, a simulation framework for mono-frequency radar systems such as in [10] provides valuable insight into the underlying mechanisms of vital sign detection. Although mono-frequency models cannot capture range-dependent effects or multi-target scenarios, they provide a controlled environment to investigate fundamental performance limits and sensitivities of radar-based vital sign detection. As such, they form an essential building block for understanding and validating more complex multi-frequency radar systems. This separation

of effects enables a structured decomposition of uncertainty sources. While mono-frequency simulations primarily capture physical and environmental contributions, multi-frequency simulations extend the analysis to include range-dependent effects and signal processing contributions. Together, these approaches provide a hierarchical framework for uncertainty analysis, ranging from fundamental physical limits to full-system behaviour.

Measurement with a stepped-frequency continuous-wave (SFCW) radar under laboratory conditions

To illustrate the discussed principles and their practical implications, the following section presents experimental results obtained with a stepped-frequency continuous-wave (SFCW) radar system under controlled laboratory conditions.

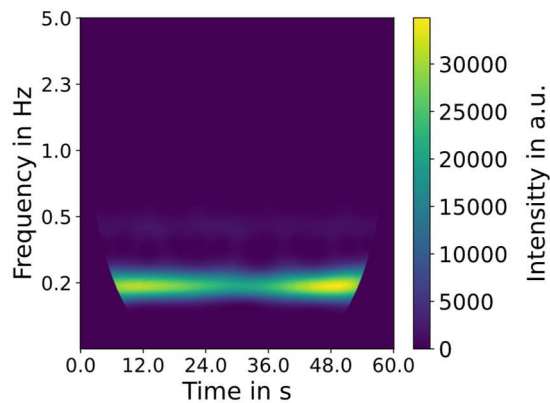


Fig. 3: SFCW-based respiration rate measurement with a controlled breathing dummy (mechanically moving plate).

Three examples are given in Fig. 3 to Fig. 5, using an SFCW radar operating at 2.4 to 2.5 GHz in an on-site RF testing chamber. This specific radar allows for the adjustment of the frequency steps, per-frequency time-domain sampling points, internal range-bin processing and adjustable transmit power and receiver attenuation. In the example, a test subject was hidden behind a pile of building debris of an approximate depth of 1 m consisting of ceramic tiles, with the radar scanning the subject in forward- and backward-facing positions; all other parameters remained unchanged. The spectrogram was obtained using a continuous wavelet transform.

In Fig. 3, a measurement was performed using a moving plate with a fixed rotational frequency, mimicking the respiratory chest excursion induced by survivors. Here, the “respiration rate” of $f_{\text{resp}} = 0.2$ Hz can be clearly seen in the

spectrogram for the entire duration of the measurement.

In Fig. 4 and Fig. 5, measurements were performed with an adult male test subject instead of the dummy. It can be observed that the orientation of the test subject significantly influences the detectability of the respiration signal. In the backward-facing position, the breathing frequency of the test subject is, while still recognizable, subject to a weaker SNR and thus harder to detect compared to the forward-facing measurement. In quantifying the measurement uncertainty, this is one of many relevant factors.

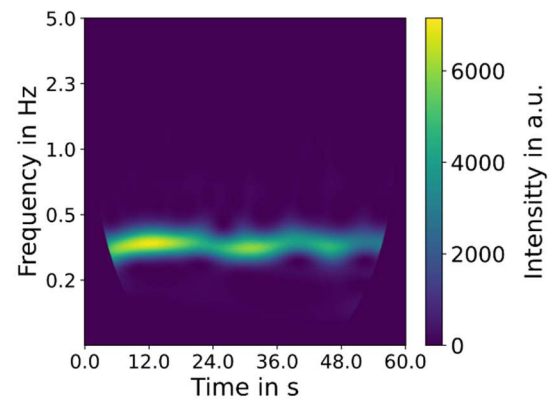


Fig. 4: SFCW-based respiration rate measurement for a forward-facing anteroposterior position.

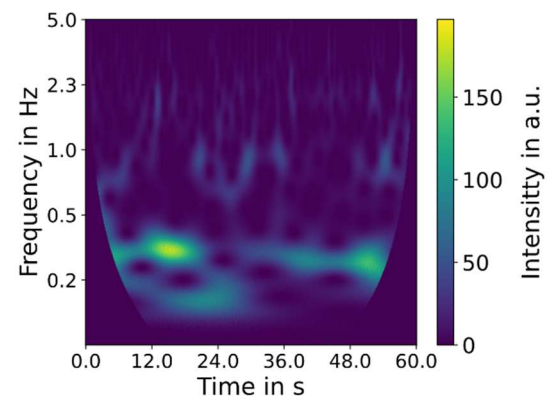


Fig. 5: SFCW-based respiration rate measurement for a backward-facing anteroposterior position.

Field measurement with FCCW radar

Additional experiments were carried out under field conditions using the FCCW radar system described in [7], as depicted in Fig. 6. The radar system was mounted on a DJI Matrice 400. A measurement time of 55 s was used. In the following experiments, the analysis is performed on individual range bins. In

particular, range bin 1 corresponds to the closest spatial interval (covering the range from 0 to 2.5 m), where the strongest reflections from nearby targets are expected. Therefore, a detectable respiration signal in range bin 1 indicates that the target is located in close proximity to the radar.



Fig. 6: Field tests with a DJI Matrice 400 drone, using the mechanically moving aluminium-coated plate as a breathing dummy. Here, bags with ceramic tiles are used as obstructions.

Fig. 7 depicts the FFT spectra for different range bins obtained from a measurement with a stationary UAV placed on the table. The breathing dummy respiration rate was set to $f_{\text{resp}} = 0.5$ Hz. This respiration rate is successfully detected, as evidenced by the prominent spectral peak in range bin 1, covering a range of approximately 0 to 2.5 m.

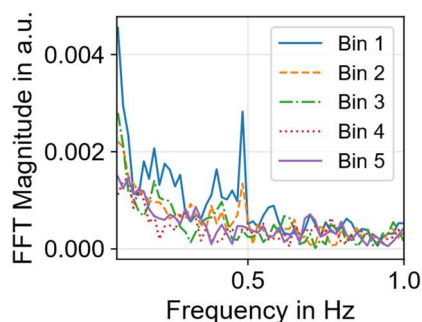


Fig. 7: FFT spectra of a measurement with the FCCW radar for a stationary UAV placed on the table with wooden/Styrofoam obstructions.

This breathing frequency becomes obscured once the UAV is in motion, as depicted in Fig. 8. Due to the UAV motion, the radar cannot clearly extract the breathing frequency from the echo signal. Without motion correction, the measurement uncertainty increases significantly, as motion-induced phase variations mask the respiration signal.

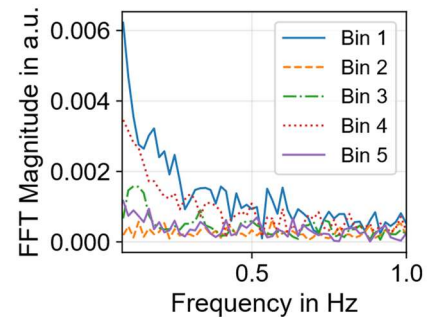


Fig. 8: FFT spectra of a measurement with the FCCW radar for a UAV at an altitude of 5 m above the table with ceramic tile bags as obstructions.

Expected impact

By producing quantitative uncertainty budgets, ZeMeRGe enables meaningful reliability statements (e.g., confidence that a detected respiration signature corresponds to a human), optimisation trade-offs for UAV operation (speed vs. accuracy vs. battery life), and safer and more efficient deployment for first responders. The project's results will make bioradar technology both more effective and scientifically verifiable, turning it into a trustworthy decision-support tool for disaster relief. In particular, the presented analysis highlights the need for motion compensation and scenario-dependent calibration to achieve reliable operation in real-world deployments.

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