Next Generation NDE Sensor Systems as IIoT Elements of Industry 4.0
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ABSTRACT
Industry 4.0 (I4.0) describes the current revolution of the industrial world with a strong impact on the complete production sector. Data about production processes and the corresponding material and product status are the key elements. All over the world, the protagonists of I4.0 are facing the challenges to define appropriate concepts for I4.0 infrastructure, data exchange, communication interfaces and efficient procedures for the interaction of I4.0 elements. The role of future Nondestructive Evaluation (NDE4.0) and corresponding workflows (i.e. data generation and evaluation) will change accordingly. Thus, NDE4.0 systems will be elements of the Industrial Internet of Things (IIoT) that communicate with the production machines and devices. They become an integral part of the digital production world and the industrial data space. This paper is a summarized overview of our current developments as well as of general key technologies and future challenges to enable the paradigm change from classical NDT toward NDE4.0, starting with approaches on signal processing, artificial intelligence-based information generation and decision making, generic data formats and communication protocols. For illustration purposes, prototypical implementations of our work are presented. This includes a pilot development of a modern human-machine-interaction by the use of assistance technologies for manual inspection.

KEYWORDS
NDE4.0; cognitive sensor systems; IIoT; signal processing; compressed sensing; relevant data; I4.0 interfaces; communication protocols; human-machine-interaction (HMI); trusted AI

1. Introduction and General Motivation: The Transformation Toward NDE4.0 and the Requirements for Smart NDE4.0 Sensor Systems as Elements of IIoT

Industry 4.0 (I4.0) describes the current revolution of the industrial world with a strong impact on the production industry. The availability of comprehensive data about production processes and the corresponding material and product statuses is one of the key elements for this digital transformation to happen [1]. Whenever a material is changed (whether deliberately or by uncontrolled external influences) and this change is detected, the current state of a product is stored by NDE4.0 systems in the digital product memory. Such a product
memory can be fed via the entire lifecycle of a product, as depicted in Figure 1 (i.e. from “cradle to grave”).

This individualized smart material information can be used for value-added digital services and cross-optimization in the concept of circular economy. This concept is depicted in Figure 2. In the context of its implementation in I4.0, the circular economy is mainly based on the crosslinking of the three core elements: smart machine, smart production and smart services. This enables new functionalities to be realized, such as data exchange, self-optimization, traceability, predictive maintenance, remote control and online services. Moreover, the digital material memory reflects the cyber-physical representation of the material or product and allows for accessing the digital material fingerprint of a product within the I4.0 ecosystem.

For an integration of smart nondestructive sensor systems into the digital environment of a smart fab, recent developments in industrial communications toward the industrial internet of things (IIoT) can be leveraged. IIoT-enabled smart sensor systems are key elements for the digital revolution of industry (i.e. for I4.0). In this sense, smart nondestructive sensor systems (i.e. NDE4.0 sensor systems) are expected to become an essential part of the I4.0 world thereby giving access to the relevant data about products and processes.
To this end, we need completely new concepts to manage the extraction of these relevant data instead of big and “meaningless” (i.e. highly redundant) data. This basic design philosophy has to be implemented starting from the technology level (i.e. microelectronics) up to the data analytics level (i.e. data management space). NDE4.0 sensor systems should supply only relevant information and as such contribute only with value-added data to the industrial data space. In order to contribute to the data and platform specifications and for establishing special use cases from the NDE domain, the NDE4.0 expert group of the German Society for Nondestructive Testing (DGZfP) has joined the International Data Spaces Association (IDSA). The IDSA platform and the IDSA consortium are managed by the Fraunhofer Society.

Of course, data exchange and communication within I4.0 also need compatible standards for NDE4.0 data, as well as for communication protocols, for software and hardware interfaces and for digital service platforms (data management platforms). This is reflected by the different layers and data levels of the Reference Architecture Model for Industry 4.0 (RAMI4.0) from the shop floor up to the enterprise level [2]. RAMI4.0 is discussed in detail in section 4. Our customized approach for NDE4.0 also follows this general concept for implementing a reference architecture for industry 4.0.
In total, NDE4.0 describes the paradigm shift in the underlying concepts for the digital revolution in NDE, i.e. for the design, the overall workflows as well as for the functionality and the procedures how nondestructive sensor systems are acquiring and supplying data about materials and processes. Moreover, NDE4.0 will not only supply data but furthermore it generates information and knowledge, for example, by the use of artificial intelligence (AI), which is integrated in revolutionary technologies for advanced signal and data processing within NDE4.0 systems (cp. Fig. 3).

Figure 3 depicts the different steps in the data value chain. For NDE4.0 to happen we need innovations in each of these steps. However, the potential will only be explored if we carry out cross-optimization in the system design taking into account the interplay of the different stages. In our research we implement the embedding of NDE4.0 systems into digital environments through data exchange and communication via Open Platform Communications Unified Architecture (OPC UA) within RAMI architecture for I4.0, which is considered as one of the promising technologies in Germany (cf. Section 4).

In the following sections (2) to (5), new NDE4.0 developments covering several of the aforementioned aspects are explained in more detail:

1. Methods for relevant data extraction by sparse signal recovery and signal processing for various physical NDT modalities: ultrasound, X-ray, optics, nuclear magnetic resonance techniques.

2. Data processing, data fusion and data evaluation by applied AI and advanced pattern recognition for customized generation of meta-data and for decision-making.

3. R&D results for digital embedding and first prototypical implementations for NDE4.0 data formats based on DICONDE standard and communication protocol implementation in the IIoT by OPC UA.

4. Demonstration prototype for a comprehensive “Human-Machine-Interaction” System (HMI) for NDE4.0, implementing the R&D results from

![Figure 3. NDE4.0 system design along the signal and data value chain.](image-url)
The Fraunhofer system SmartInspect for assisted nondestructive testing in manual inspection.

It is worth to mention that this paper is intended to be a summarized overview of current development, key technologies and future challenges regarding NDE4.0, where we also would like to illustrate this with our developments in this field. It is not the scope of this paper to explain our developments in detail, as these will be reported in separate publications.

The technical solution for data format and communication protocols mainly reflect the outcomes of the technical committee NDE4.0 of the German Society for Nondestructive Testing (DGZfP) and the requested standards from the EU market. We are contributing to the strategic technology roadmap of DGZfP and Fraunhofer IZFP has taken the lead for the corresponding expert group NDE4.0. Current collaboration with the American Society for NDT (ASNT) and further partner associations worldwide are ongoing on the NDE4.0 topic.

2. From Big Data to Relevant Data: The Power of Sparse Signal Processing

Sparse signal processing is considered a very powerful tool for the relevant data extraction across all modalities used in NDE. We demonstrate the potential using the example of ultrasonic testing.

Ultrasonic inspection has a long-standing history, so long that it originated in a time before digital signal processing was ubiquitously available [3]. In fact, some ultrasonic inspection tasks can be carried out entirely in the analog domain, using a scope to display the voltage signal of a piezo-electric transducer element. When digital devices were introduced in the process, care was taken to make sure the digitalization would not cause any unwanted changes to the signal and it would represent as closely as possible the original analog signal. The amount of digital signal processing applied in the field of NDE in practice is therefore traditionally quite moderate and limited to some amount of filtering and similar visual aids for the inspection engineer, as well as storing and documenting the inspection processes for later retrieval.

Yet, from a theoretical point of view, the potential of applying advanced signal processing knowhow to ultrasonic signals is tremendous. First of all, the signals are highly structured. Roughly speaking, we can consider them as a superposition of (a typically small number of) dominant terms originating from reflections of the incoming acoustic signal, diffuse components due to scattering, diffraction, and speckle, as well as noise components caused by the receiver electronics. This implies that a significant fraction of the signals’ energy has a sparse representation, i.e., it can be expanded on a known basis with only few basis vectors. Based on this representation, we can significantly compress ultrasonic data. This leads to a highly reduced data volume, which
can also facilitate its later processing in order to enable real-time operations. In addition to this temporal structure, the spatial correlation of the signals is quite significant as well, since the acoustic wavefield inside a homogeneous section of material is a continuous and smooth function. This allows a considerable amount of spatial subsampling as well which reduces the number of channels we actively need to sample to obtain a unique image.

These benefits have of course been discussed intensively in the past already, in particular in the medical ultrasound community. Postprocessing of digitally sampled ultrasonic data was already discussed in the 70s regarding spatial filtering [4], deconvolution via inverse filtering in time [5], and Cepstral processing [6], respectively. Deconvolution techniques became increasingly elaborate with the growing availability of digital signal processing power [7–9]. With the advent of the field of Compressed Sensing (CS) after the seminal papers by Candes and Tao [10], the field of sparse signal processing was revived and a sparse perspective on deconvolution techniques led to a slightly different view on deconvolution techniques as well [11–14]. Based on these concepts, inversion techniques with sparsity-aware regularizers were discussed more recently [15–17]. Regarding the exploitation of spatial correlation for sparse arrays for ultrasound, this was already discussed in early publications more than 20 years ago, cf. [18]. With a growing research interest in sparse techniques due to the rise of the CS theory, the optimal array design and the corresponding signal processing algorithms have been an active research topic since then [19–22]. CS itself was applied to medical ultrasound in various flavors more recently, e.g., in [23–26]. Some first applications in NDE have appeared as well [27–30], but these are much scarcer.

One is still beginning to explore what appear to be intimate connections between these ideas and the field of NDE4.0. One of its major themes is that our approach for acquiring and treating digital data should change fundamentally. One should stop considering our sensing equipment as a mere tool for acquiring ever-growing amounts of digital data but instead move to recording and processing information, data enriched by prior knowledge on the inspection task, previous observations, reference data and all the augmentations our smart industrial environments will have to offer in the future [31].

This process is required to be carried out on many levels and it starts already in the basic sensing level. The traditional approach to building sensors is to sample signals at the Nyquist rate in all dimensions to make sure one does not lose any important signal contribution. For ultrasound signals that extend over time as well as two or even three spatial dimensions, this can lead to excessive amounts of data due to the potentially large number of channels that need to be sampled in parallel. For systems that are monitoring a big number of processing steps in a smart fab, this can result in massive amounts of data that need to be stored and maintained. In addition to the burden this puts on the data storage, finding the relevant piece of information will become increasingly difficult as
well – one may have to resort to big data techniques just to manage all the data our sensors have created. Then again, as discussed above, not all of this data is relevant since it is indeed highly structured and thus redundant.

Therefore, one obvious solution to this dilemma is to fundamentally change the way the digital data are acquired. By equipping our sensors with more intelligence, one should enable them to make their own decisions on what part of the data is relevant. In so doing, one can reduce the data volume already in its earliest stage, upon its creation, to make sure the degree of redundancy is reduced, and only relevant data is recorded.

One may be led to believe that the idea of data reduction contradicts with the ever-growing need for data to feed the data-hungry processes that underpin the training of up-to-date artificial intelligence architectures such as deep neural networks, which we discuss in detail in the subsequent section. However, note that we only seek to avoid recording irrelevant data and as it is irrelevant to the inspection task it is also not necessary for the training of models that operate on these data. The relevant excerpt of the data is maintained and in so doing, the training of neural networks will not be impaired.

While such ideas may sound obvious at first sight, it is difficult to underpin them with a solid theoretical foundation that makes exact predictions on the degree of information content in a signal and the required number of samples to capture it. At this point, we believe that the CS framework may provide very helpful insights toward this goal. As an example, let us consider the Finite Rate of Innovation (FRI) theory [32], which can be considered as a predecessor of CS. In FRI sampling, it was shown that the required number of samples per unit of time only depends on the unknown degrees of freedom per unit time, which makes it independent of physical quantities such as the bandwidth. For instance, if a signal is composed of a superposition of weighted and shifted pulses where the pulse shape is known then for each pulse there are only two unknowns: its shift and its weight. Hence, if one knows that within a given time frame, no more than \( K \) pulses can appear, the signal only has \( 2K \) degrees of freedom for that time. FRI sampling then proves that there exists a sampling strategy with only \( 2K + 1 \) samples taken in the same time frame, such that the entire signal can be recovered without any loss of information [32]. This is highly relevant to ultrasonic NDE where the presence of a superposition of weighted and shifted pulses is a common assumption and such an approach breaks the typical trade-off between required sampling rate and timing accuracy. In practice, some assumptions have to be generalized. For instance, the pulse shape is typically not exactly known and it may vary significantly in fact, e.g., due to the sensors’ transmit/receive angular dependence, frequency-dependent attenuation, frequency-dependent reflection patterns from the interacting objects, etc. However, experimental results show that despite these influences, significant data reduction can be achieved by virtue of compressed sensing. This example clearly shows the way of thinking that
underlies the CS approach in ultrasound: sample only what is not known yet, avoid sampling pieces of the signal that are already known.

CS provides a general toolbox for treating this problem. In addition to guarantees for required sampling rates, it provides guidance on how to construct the sampling strategies and how to reconstruct the compressed signals. Some of the resulting techniques have actually been around before and could thus be seen as mere rediscoveries. However, their connections to the solid CS theory provide a new level of understanding about the performance and the limits of certain techniques. Therefore, we see advanced signal processing techniques that are inspired by the CS framework as one of the key enablers to empower the sensors of the future in order to be capable to meet the demands NDE4.0 will put on them.

So far, we mostly discussed the application of CS to the field of ultrasonic NDT. However, it can be applied to many other modalities as well. In fact, it originated in optics, where the goal was to build a camera for wavelengths where detectors are difficult and expensive to build such as near-infrared or even far-infrared. The goal to save on the number of pixels fits very well with the CS philosophy. And indeed, it was shown in [33] how CS ideas can realize a camera with just a single pixel based on programmable arrays of micro-mirrors, a radically new way of performing imaging compared to existing approaches. In parallel, CS-based imagers were developed based on random lenses [34] or pseudo-random masks behind the lens [35], see [36] for a survey. These examples show just how much out-of-the-box thinking may have to be applied to design CS-based sensor systems. Note that CS was also very successful in Magnetic Resonance Imaging (MRI) [37] where recently, all major vendors have integrated CS into their medical MRI scanners for the clinical practice. A few years later, similar breakthroughs in X-ray were also reported [38]. These can be translated to very relevant benefits for NDT, such as a cycle-time reduction for CT-based inline inspection by a factor of 4–8 without compromising defect finding capabilities, as shown in [39].

Let us discuss a few concrete potential applications where we expect these ideas to be demonstrated in the near future. One promising candidate is given by the field of Structural Health Monitoring (SHM) [40]. In SHM applications, sensors continually monitor certain critical components and structures to gather data related to its condition. This means that a significant amount of prior knowledge is available before each measurement. In particular, the expected signal for a “healthy” component is known and there is no need to measure this known signal again as explained in [41]. Instead, the sensor can focus on the deviations from this signal and measure those directly. This is an example of a “cognitive” sensor that can decide via its own intelligence which signals shall be measured and how to carry out the measurement. Applying this concept can lead to a significant reduction of irrelevant data, which aids the further analysis and processing of a now reduced data set. The potential benefits of this approach are even more extensive when sensors are connected in a sensor network and
can share their knowledge and decisions with each other. Advanced data fusion and machine learning-driven decision-making techniques can then be leveraged to enable the system to not only monitor the state of individual structures, but also infer about their interdependencies and thus the evolution of the system as a whole. Once such techniques are deployed, there is a strong tie to the later signal processing stages, which can greatly benefit from the improved degrees of freedom offered by the sensing stage. Exploiting the prior knowledge on both levels (sensing and processing) leads to improved capabilities in reconstructing and evaluating the results at a later stage. In addition, working with a reduced (relevant) data excerpt bears the potential for significant speedups compared to traditional sensing and processing approaches.

Another example is given by the measurement design for spatiotemporal sampling strategies. Currently, the Full Matrix Capture (FMC) as well as the Plane Wave Imaging (PWI) techniques receive a considerable amount of attention due to their ability to carry out ultrasonic imaging with very good contrast ratios and high speeds [42]. Yet, scaling these techniques to arrays with a larger number of transducer elements is still a big challenge due to the large quantities of data that need to be processed in real-time. Here, CS-based data reduction technique could offer a significant relief in reducing unnecessary data to facilitate their later processing. Figure 4 illustrates an example for data reduction in an FMC setting. For this example we consider a 16-element array (the middle section of a 64-element array with a sensor pitch of 1.8 mm) on a 12 cm high specimen with side-drilled holes in a diagonal arrangement shown on the left side of Figure 4. The red dashed lines give a rough indication of the total illuminated area though the insonified energy decays rapidly to the sides so we cannot expect all the defects within this area to become visible. For the FMC acquisition, each transmit element sends a pulse sequentially and for each transmitted pulse at a frequency of around 4 MHz, the received A-scans at all 16 elements are recorded with a sampling frequency of 80 MHz. The reconstruction of this data with the total focusing method (TFM) is shown in the middle plot of Figure 4. We then applied compression of the data in time domain (factor 7.4) as well as the spatial domain (factor 12.8) leading to a total compression factor of 94.8 (see [43,44] for details). The parametric reconstruction of the compressed data using the Fast Iterative Shrinkage and Thresholding Algorithm (FISTA) is shown on the right-hand side of Figure 4. FISTA is an iterative algorithm for solving l1-regularized Least-Squares problems and can in some sense be interpreted as an iterative and regularized version of SAFT. For clarity, the top row shows the results on a linear color scale whereas the bottom row shows a log scale. The result shows that a very good reconstruction is possible from about 1% of the original data with an imaging quality that is superior to FMC, which demonstrates the high degree of redundancy in the signals.

As a final example, we discuss the virtue of data reduction for real-time processing of ultrasonic data in the context of manual ultrasonic inspection, in
particular with respect to the SmartInspect system developed at Fraunhofer IZFP, which we describe in detail in section 5. Regarding relevant data extraction and sparse signal processing we analyzed how far the recorded A-scans can directly be processed to reduce their data volume and convert them into a more meaningful representation, such as a (pseudo) reconstruction that can be computed on-the-fly. We have shown that this is possible based on the concept of Fourier sampling \cite{44}. In Fourier sampling, we use the fact that shifted pulses in time domain translate to a superposition of pulse spectra weighted by appropriate phase terms in frequency, so that in theory, every Fourier coefficient within the pulses’ bandwidth contains information about all the pulses’ delays and amplitudes. Therefore, sampling a few Fourier coefficients allows us to extract all delays and amplitudes in the data. This idea is related to the Xampling concept, which presents a system architecture designed for compressed sensing of analog signals. Xampling methodology behind the CS architecture for medical ultrasound is discussed in \cite{23} with the difference that \cite{23} measures linear combinations of Fourier coefficients by sampling the signal after appropriately designed filter kernels whereas we measure Fourier coefficients directly \cite{44}. After the Fourier coefficients have been obtained, we can employ a concept similar to beamforming for providing an image: a set of potential point sources on a virtual imaging plane is

Figure 4. FMC example. Left: original piece with 64-element on top. Central 16 elements that were used for the FMC snapshots are marked along with their approximate field of view. Middle: classic reconstruction (using the TFM algorithm) from Nyquist-sampled data set using TFM (top: linear scale, bottom: log scale). Right: parametric reconstruction (using the FISTA algorithm) from compressed data set, using a factor 12.8 spatial compression and a factor 7.4 temporal compression, i.e. even superior quality in the reconstruction result with only about 1% data expenditure (top: linear scale, bottom: log scale).
generated and for each point source, the spatial-matched filter to the observed Fourier coefficients is computed. The magnitude of the matched filter provides an intensity that is displayed as a pseudo-reconstruction. It closely resembles a C-image obtained from a 3D reconstruction but can be computed directly and is thus very fast to execute.

Therefore, its computation can be carried out in real-time during the manual inspection. An example of the raw data compared to the pseudo-reconstruction is shown in section 5, underlining how much the pseudo-reconstruction improves the feedback quality compared to the raw data. Note that for this example we used only a single Fourier coefficient, corresponding to a data reduction by a factor of more than 1000.

Overall, these examples show that the application of CS-based signal processing techniques bears significant potential to reduce big data to relevant data in the early processing stages. Yet, these examples only mark the beginning of the discovery of an entire field of potential innovations that is so far unexplored. Going from collecting massive amounts of big data to just the right amount of relevant data is not just a nice feature, it is inevitably becoming a necessity, which will require to radically change our mind-sets in how we deal with data. This is a process we are still exploring and through initial example applications, we are starting to build our confidence in the process.

However, this is an effort that cannot be mastered by a small group of researchers alone; it will require global collaboration over the entire field of NDE4.0 to put this vision into practice and fully explore its potential.

3. Applied AI for Automated Data Analysis/evaluation of NDE4.0 Sensors

Automated defect detection and decision-making methods have been used in various nondestructive evaluation and structural health monitoring systems for a long time. However, the data processing and analysis methodologies are mostly still rather traditional in the sense that they rely on simple decision algorithms such as heuristic-based (filtering, thresholding, etc.) or reference-based segmentation [45–47]. In more demanding operational environments and for the inspection or monitoring of complex components or processes, the expert human inspectors are still “more trusted”. It is assumed that they can achieve far superior inspection results compared to the simplistic computer-based methods. Consequently, in most of these inspections, human experts currently still perform the data analysis, even when the data acquisition itself is largely automated. Such human-based evaluation is time consuming, cost intensive and offers no solution for a fully automated monitoring and evaluation system compatible with the NDE4.0.

The human inspector performs sophisticated interpretation that cannot be sufficiently described through simple algorithmic processing steps. The inspectors sharpen their skills through years of training (learning) and utilize
various data characteristics in their judgment (such as signal dynamics, image contrast, etc.). Machine Learning (ML) can be used in the cases where a direct algorithmic description is intractable. The recent improvements in ML algorithms especially in Deep Learning (DL) and the corresponding computational tools have enabled more complex and powerful models that reach near human-level performance in tasks like object recognition, driverless cars, robotics and machine translation. Modern deep architectures have achieved impressive results in many tasks, such as image classification [48] and object detection [49].

Concerning the current state of the art for using machine learning in NDE, these methods can be clustered into two distinct approaches. Firstly, modern shallow (i.e. not deep) ML models (e.g. random forests [50] or Support Vector Machines SVM [51,52]) with advanced feature engineering are used with the aim to develop computationally lightweight models that can be implemented on-the-fly to aid the inspector in manual inspection. Secondly, data-driven DL approaches using convolutional neural networks (CNNs), U-Nets, etc., [53–59] are used to learn from raw NDE signals without the need for explicit features engineering. The recent work on deep models takes full advantage of advances in models developed for other applications and shows good results across different NDE fields. However, there are still many obstacles for the full-scale application of DL in NDE field, mainly is the lack of representative datasets, the expansibility and trust in the DL decisions.

In fact, a massive obstacle for using powerful DL models in NDE has been the limited availability of training data. Acquiring sufficiently representative NDE dataset requires manufacturing a large set of reference defective specimens as well as measuring in realistic operational conditions. This can quickly become infeasible. We see two key aspects to progress beyond this (1) by learning from synthetic data and (2) by applying the data augmentation approach in the NDE field. This latter technology is a key tool for successful application of DL for small datasets in other AI applications. Furthermore, for the application of AI/ML algorithms/models to NDE data, it is equally problematic that no common generic data formats have yet been established worldwide. However, there are joint efforts to introduce such uniform generic data formats into the NDE world (see section 4). The current lack of uniform data formats in the NDE sector is an obstacle for application of AI in this field. Transfer learning is another possibility to overcome the obstacle of limited representative NDE data by considering pre-trained network models and adapting them for the specific NDE or structural health monitoring (SHM) application.

A further key requirement for the adoption of DL models for NDE4.0 is finding means to explore and to explain the decision made by the models, i.e. explainable AI. This will increase the trustworthiness and acceptance of the models. The aim here is to demonstrate that the DL models learn similar
patterns as a human inspector uses and base their decisions on these patterns (hot spots).

Today, most of the deep models such as CNNs are still considered “black boxes”, that lack transparency and therefore cannot be fully trusted by a human user when it comes to crucial decisions which is the case for most NDE applications. What’s worse, they may also become quite vulnerable to adversarial examples [60]. With explainable AI methods, a human understandable explanation could be acquired from a typical “black box” model. Some approaches are investigated to address this problem, such as the saliency map generation approach [61], where the saliency map of the input data, indicating which signal part contributed more to a certain output decision, is generated using the internal parameter of the deep neural network. In the NDE area, a decision of “error”, “no error” made by a well-trained model in most cases cannot satisfy an end user. If an error occurs, detection of the error is indeed important, while an explanation and understanding about the reasons and causes standing behind the decision-making are of the same importance for error documentation and error analysis. Therefore, the explainable AI is drawing more attention in NDE4.0.

Recent work at Fraunhofer IZFP in the application of AI to NDE inspection tasks addresses the automated evaluation of infrared data of fuel cells using deep learning method [62]. Traditional hand-crafted segmentation combined with SVM and random forest classifiers failed to deliver low false positive rates for the considered application. The data-driven approach with the proposed U-Net architecture strongly outperforms the traditional approach. A detection accuracy over 98% is reached.

The work in [59] explored the potential for employing Long Short-Term Memory – Recurrent Neural Networks (LSTM-RNN) deep learning architecture designed for temporal sequences to classify common defects present in honeycomb-structured materials, including debonding, adhesive pooling, and liquid ingress.

Thermal contrasts over time in the cooling process were used as input to train and test the LSTM-RNN model. Sensitivity was greater than 90% for both water and hydraulic oil ingress from the testing data of an independent experiment. Classification sensitivity was greater than 70% for debonding and adhesive pooling defects, which have had a cooling process similar to sound areas.

Another challenging application for AI was to find automated solution that can efficiently replace a human expert “A” (over 15 years of experience) in validating the assembling process and quality of cutting units [63]. Given that the experienced inspector (expert “A”) can tell the quality of the cutting unit from the sound that it makes during running, we recorded and analyzed the sound when the machine runs. A fully automated quality monitoring system with embedded AI-evaluation algorithm was developed, which outperformed
the classification performance reached by the human expert “A”. The comparison was done on the same input dataset.

4. Challenges and Requirements for NDE4.0 – Reference Architecture, Data Formats and Interfaces

The digital transformation in the course of NDE4.0 requires new approaches and methods in many technical areas, as well as in the context of research and development [64]. This is needed to generate added values from the information flow of modern production processes with the help of networked communication-capable system and sensor components. However, the development of standardized digital infrastructures is also urgently needed to open up new (digital) services (“smart services“). For the successful implementation of this digital transformation, a reference architecture for I4.0 must be considered. This enables the structuring of fields of development and application and allows connections to be established.

The Reference Architecture for Industry 4.0 (RAMI 4.0) is a globally accepted and applied model that is also used in our NDE4.0 approaches. It consists of a three-dimensional coordinate system (Fig. 5), which contains the essential aspects of I4.0 [2].

With RAMI 4.0, complex relationships can be broken down into smaller manageable packages, so that I4.0 technologies can be systematically classified and further developed. In one dimension of RAMI 4.0, the different functionalities of a factory or machine are arranged in the form of hierarchical levels from IEC 62.264. IEC 62.264 is an international standard for the integration of enterprise control systems [65], which was extended in RAMI 4.0 with the functionalities: product (“Product”; Fig. 5) and the connection to IIoT (“Connected World“; Fig. 5). The structure of the functionalities is based on and limited by hardware and includes, in addition to the product and the connection to the IIoT, the entire functionalities of a factory/machine from the enterprise over work centers, stations up to field devices. A further dimension represents the product life cycle based on IEC 62.890 for life cycle management [66]. In addition, a distinction is made between market-ready products (“Instance“) and product developments up to prototype production (“Type“). With the help of the third dimension, six layers are integrated into the model, representing the digital analogon of the machine. The six layers represent physical things in the real world so-called “Assets“ (“Physical Things“), transition from real to digital world (“Digitalization“), access to information’s (“Communication“), necessary/relevant data/information (“Data“), functions of the “Assets“ (“Functions“), organization and business processes (“Business Processes“) (Fig. 6).

Another necessary component of the digital transformation toward NDE4.0 are standardized generic data format interfaces. This is necessary because at
the present time, in the development of software and hardware for sensor/sensor systems for the nondestructive acquisition of material data, some of the software and hardware components are still using and implementing their special and thus individual data formats and interfaces. This complicates the compatibility between these developments/sensor systems enormously and makes the compatibility impossible in many cases without major adaptation efforts. Furthermore, such an incompatibility can lead to the fact that the possible added value of combining several systems, e.g. to a hybrid approach, cannot or only with difficulty be implemented. Even in the case of long-term storage of measurement, testing and monitoring data along with the associated documentation (metadata), non-uniform data formats make it difficult to generate and thus to benefit from existing added value from the data, especially when the documentation of the data formats is not linked to the acquired data.

A uniform data format for the holistic storage of all NDE data (including metadata), which is relevant in the industrial as well as in the research area, is the DICONDE format [67]. Many NDE expert groups such as the DGZfP-NDE4.0 expert group and the IDSA recommend DICONDE as the generic data format to be used in the NDE field. Thus, DICONDE is currently considered in Germany as a uniform generic data format for the NDE sector and has been introduced as a standard to be recommended. In addition, there is also a discussion consensus on DICONDE as a uniform generic data format with other countries based on the DGZfP and IDSA expert groups on NDE4.0. Other European countries seem to adopt this format, as it ensures that action-determining information for process optimization in and along the entire product life cycle can be obtained through intelligent data management and

Figure 5. Three-dimensional reference architecture for I4.0 (RAMI 4.0) [acc. to www.plattform-i40.de/www.zvei.org].
processing from the NDE data completed with metadata. DICONDE was developed as an open standard by the international standardization organization “ASTM International”. The acronym DICONDE stands for Digital Imaging and Communications for Non-Destructive Evaluation. DICONDE is an extension of the medical exchange and documentation format DICOM (Digital Imaging and Communications in Medicine) for nondestructive material data acquisition [68]. Since its development, the DICONDE format has undergone a continuous expansion to more and more specific NDE areas.

For example, special extensions have been developed for ultrasound [69], digital radiographic methods [70], computed radiography methods [71], X-ray computer tomography [72] and eddy current [73]. The format allows the storage of information such as image or volume data as well as additional information such as surface definitions and other metadata. DICONDE standardizes both the format for data storage and the communication protocol for data exchange and we will integrate this interface into our next generation NDE4.0 sensor systems, caused by the growing acceptance in the I4.0 and especially in NDE4.0 community. DICONDE thus offers a data exchange and storage format for the holistic digital documentation of signal, measurement and test data and results and additionally includes the associated metadata. Therefore, we will transfer this format to our already existing data by means of self-programmed software converters in order to be able to bring these valuable data into the NDE4.0 world.

Figure 6. Layer architecture of RAMI 4.0 [acc. to www.plattform-i40.de/www.zvei.org].
OPC UA (Open Platform Communication Unified Architecture) has established itself as a standardized interface for the connection and communication of intelligent and auto-adaptive sensor systems in I4.0 networks (cf. Fig. 7). This is the cause for us to select OPC UA as our interface for new intelligent sensor system developments [74,75]. OPC UA is a platform-independent service-oriented structure for data exchange that can serve as a basis for the development of intelligent and IIoT-capable sensor systems. It offers the possibility to implement communication interfaces with which independent connections of machine-to-machine interactions can be established. OPC UA represents a server structure for communication protocols and industrial bus systems like Process Field Bus (PROFI-BUS), Modbus (communication protocol according to Gould-Modicon), PROFI-NET (Process Field Network), etc. The communication structures and protocols used on the shop floor/factory floor level remain the same, since devices connected via OPC UA use the OPC server as a gateway. OPC UA can be used to replace and/or supplement classic fieldbus systems (Fig. 7).

With the help of data infrastructure and server facilities for the fast and secure transport as well as for the distribution/networking/storage of digitalized sensor and material data, we are in the process of building and establishing a management platform and thus generating benefits from the data and information flow. Integrated into this platform are developments of digital interfaces and possibilities for intelligent data storage, processing and analysis (ML, AI, etc.), which will be tested and thus validated with our existing data as well as with data from customers. This and the NDE-know-how already available at Fraunhofer IZFP will provide novel (combination) possibilities in the future with regard to digitalization, optimization and modernization of existing testing...

Figure 7. Data management hierarchy for I4.0 and smart factory – communication interfaces for NDE4.0 devices on a hardware level (factory floor and programmable logic controller PLC) and on the data management level for production and enterprise control (Supervisory control and data acquisition SCADA/HMI, manufacturing execution system MES, enterprise-resource-planning ERP) [acc. to www.vdma.org].
tasks within the framework of a modern platform solution. Furthermore, our chosen approach supports the development and application of hybrid testing technologies as well as the sustainable and secure handling of the data. Innovative concepts and latest developments of our current and future sensor systems can thus be embedded in the I4.0 landscape.

5. SmartInspect System: Demonstration Platform for a Comprehensive “Human-Machine-Interaction” System for NDE4.0 and for IIoT-integration

Fraunhofer IZFP has developed a flexible NDE4.0 platform concept that consists of several complementary technology modules. Each of them demonstrates different features and innovations for future NDE4.0 devices and sensor systems (cf. Fig. 8) as well as options for a beneficial integration in the IIoT. The system allows for continuous and specific R&D in order to improve the individual modules and to investigate options for various application scenarios in the context of NDE4.0.

Generally speaking, the laboratory prototype system is our R&D approach to gain experience and advanced knowledge about the way of developing and implementing required features for future NDE4.0 sensor systems. Together with partners from industry, the lab prototype is used as a proof of concept in specific applications of NDE4.0 sensor systems, e.g. for automated quality management in production processes in the industry (smart factory) or for revolutionary procedures in the digital work-flow for manual inspection jobs. In general, the options for the integration of the SmartInspect system as an IIoT-element are currently under investigation in various domains of the industry and the corresponding data spaces. On one side, the modules of the system can be used for NDE4.0 devices in completely automated and digitized

![Figure 8. Fraunhofer IZFP SmartInspect system: assistance system with integrated modules and interfaces for NDE4.0 sensor systems and innovative features for signal processing and real-time visualization using augmented reality (AR).](image-url)
applications of smart factory concepts (sensor-to-machine communication) and on the other side, the SmartInspect system contains as well interfaces for innovative interaction with users (such as speech recognition or AR glasses). In this respect, SmartInspect is an intelligent assistance system (cf. Fig. 9) that is designed especially to support and to help inexperienced operating personnel (human-machine-interaction HMI for NDE4.0).

In particular, the platform contains procedures (implemented in hardware components, microelectronics, software and firmware, see Fig. 9) for:

- advanced signal processing and sparse signal representation (for general description cf. section 2),
- interfaces and data formats for the IIoT-integration like OPC UA and DICONDE (for general description cf. section 4) demonstrated for Fraunhofer IZFP ultrasound, eddy current and micro-magnetic NDE4.0 sensor hardware and electronics,
- use of innovative procedures based on AI and advanced pattern recognition (cf. section 3) for data analysis in combination with new developments for high-performance algorithms for signal processing and image reconstruction, e.g. real-time progressive synthetic aperture focusing technique (SAFT) applied to manual arbitrary scanning operation in ultrasonic inspection,

![Figure 9](image)

**Figure 9.** Fraunhofer IZFP SmartInspect system – NDE4.0 modules for IIoT integration and innovative HMI features. 1. optical sensor tracking
2. speech control
3. digital NDE twin
4. intelligent signal control and real-time processing: signal processing, defect reconstruction, visualization using AR and data transfer via internet
5. HMI feedback for sensor handling
- optical sensor tracking (using standard video camera) closely linked to the NDE data acquisition electronics.

The system has the following capabilities and features (Fig. 9):
- autonomous signal control and self-monitoring/self-surveillance for safe operation
  (for example: complete covering of inspection and scan region, auto-adaption of configuration parameters),
- signal processing and signal control in order to guarantee that only valid raw data are recorded, e.g. to avoid incorrect sensor coupling, liftoff, sensor tilt, etc.,
- augmented reality (AR) and real-time visualization of processed signals or evaluated data (real-time overlay of inspection results fused with the real-world video image),
- remote control and data transfer via internet (option to transport the evaluated NDE result via internet nearly in-situ to a remote observer/remote expert or to the customer),
- “bio-feedback” and interaction of the NDE4.0 sensor with the operator (HMI): possibility for an untrained operator to react immediately with respect to the AR-visualization of the inspection result by adapting the sensor manipulation and by correcting the manual scanning process. This feature is to guide the operator and to give direct high-level information and feedback during data acquisition.

Currently, we verify the usability of the assistance system SmartInspect for ultrasonic crack detection for the use case of manual inspection of weld seams or more general applications of UT and ET for detection of defects and inhomogeneities.

Validation is done by comparing the automated test results of the SmartInspect system with the test protocols generated by a well-experienced level 1 or level 2 UT or ET expert. During the inspection, the SmartInspect system is assisting the untrained operator to perform a correct nondestructive evaluation job by giving feedback on inadequate sensor handling (e.g. like loss of coupling, liftoff, tilt), missing scan regions or on missing raw data and signals of sufficient quality.

The feedback and support to the operator are given by augmented reality (e.g. AR glasses and displays like the Microsoft HoloLens). This enables the visualization of the calculated sound path in the specimen (ultrasound propagation) or mapping the NDE results (e.g. defects) with a semi-transparent layer onto the optical video image in real-time. The SmartInspect system is empowered with AR displays for real-time fusion of NDE results (i.e. evaluated defect reconstruction) with video images (i.e. of real images of the specimen).

Thus, advanced defect reconstruction algorithms are an essential element for real-time imaging of NDE results for flaw and defect visualization. For this,
Fraunhofer IZFP has developed completely new algorithms especially for defect reconstruction from ultrasound signals that are adapted for the arbitrary movement of a transducer during manual scanning operation. These elaborated high-performance algorithms are based on customized methods of sparse signal representation and compressed sensing (cf. section 2) in combination with well-known conventional SAFT reconstruction (synthetic aperture-focusing technique).

For UT assistance in manual inspection, visualizing the data in 2D (C-Scan) or even 3D (volumetric display, e.g., via AR display) instead of 1D (A-scan) eases the interpretation of the acquired inputs. For this purpose, advanced reconstruction methods such as progressive SAFT are integrated in the signal and data processing modules of the SmartInspect system (cf. section 2) [76]. This allows for real-time SAFT reconstruction and AR visualization of defects during arbitrary scan movement (i.e. UT data acquisition at arbitrary sensor positions tracked by the video camera). We show an illustration of this process in Figure 10.

The top row depicts a reference specimen with a height of 90 mm, several flat bottom holes as well as some oblong holes (drilled to a depth between 5 and 20 mm from the bottom). The diameters of the holes can be seen from the top-right image that displays the top-view. The bottom row shows the raw data display of this specimen with the SmartInspect system. The inspection settings were done by using an industrial single transducer of 5 MHz in contact mode and a sampling frequency for the A-scans of 80 MHz. Figure 10 shows the raw data on the left-hand side whereas the right-hand side shows the real-time reconstruction. Clearly, many of the features are not visible in the raw data including number and size of the flat bottom holes as well as the shape of the saw cuts.

Note that SAFT processing puts stringent requirements on the positioning accuracy. To this end, we have evaluated the position accuracy requirements by systematically studying the impairment of the SAFT reconstruction with respect to positioning errors [76,77]. Our results indicate that positioning errors of up to a quarter wavelength are tolerable, for larger errors the reconstruction quality becomes impaired and for errors exceeding half a wavelength they become severe. For UT in steel at a frequency around 3 MHz, this implies that the positioning accuracy should ideally be better than 0.5 mm. This accuracy can be achieved by a camera-based system that is mounted directly above the probe. In our examples, this camera would typically resolve between 5 and 10 pixels per millimeter of our test specimen, rendering sub-millimeter positioning accuracy feasible.

As we are generating only relevant data (e.g. by means of compressive sensing) the AR visualization can be streamed not only to AR displays but also to remote places via internet. NDE4.0 communication protocols and fieldbus technologies (cf. section 4) can be supplied by the electronic modules of
SmartInspect. These features offer completely new options for remote services and NDE4.0 workflows.

Another promising field of application for the SmartInspect system is for training and education in NDE, e.g. for personnel certification in level 1 to level 3. Novices in NDE learn how to handle NDE sensors and how to understand the NDE physics behind by using the assistance system. SmartInspect is giving insight to the signal propagation and the evaluation of raw data and leads to a better understanding of the relation of changes in signals to the inhomogeneities in the test specimen.

The current development stage of SmartInspect already highlights innovations in digital interfaces, signal processing and data analytics or applied AI and the embedding in I4.0 architectures. The SmartInspect platform represents a pioneer development and implementation in the continuous transition of NDE4.0 devices toward sensor intelligence devices or cognitive sensor systems. In the near future, a much higher degree of AI will be integrated in the microelectronics, the microcontrollers and in the firmware. Besides the algorithms for AI and their implementation in the microelectronics, this evolution will benefit from upcoming disruptive technologies and changes in hardware, like concepts for neuromorphic microprocessors and electronics or AI on chip. The digital age will bring disruptive changes to the NDE world and

Figure 10. Manual UT scan for defect detection. Top: specimen of 90 mm thickness with flat bottom holes and oblong holes (left: pseudo-3D, right: top-view). bottom: preview of UT raw data (left side) in comparison what a real-time progressive SAFT reconstruction would look like (right side). Only a part of the specimen was covered at this moment (i.e. current time of snapshot during the manual inspection process).
to the NDE4.0 concepts. This offers great chances for smart sensor systems in future NDE technologies.

6. Summary and Outlook

6.1. Summary

In this paper, the key technologies for progressing toward NDE4.0 are described. NDE4.0 is essential for reaching efficient and optimized material and production concepts within the I4.0 architecture and the IIoT. Core technologies for NDE4.0 systems are sparse signal representation for generating relevant data, customized AI for automated data analysis, adequate microelectronics with standardized digital interfaces, generic data formats and communication protocols. For continuous progress in NDE4.0, these R&D innovations are implemented in our SmartInspect prototype, which is evaluated for use in smart factories and as a human-assistance system.

6.2. Outlook and Challenges

While some initial promising developments in the field of NDE4.0 have already been made, we are still in the beginning of exploring its potentials. In the following, we make an attempt to give an outlook about the main challenges this field is facing from our perspective.

We can loosely categorize the challenges into four categories related to signal acquisition, AI, data exchange and standardization, respectively.

6.2.1. Challenges for Signal Acquisition

Regarding the signal acquisition aspect, the main open aspects we see are the following:

- Bringing the subsampling concepts into the sensor: While conceptually, it is evident that significant savings in terms of data rate and volume can be achieved by virtue of compressed sensing, embedding these ideas into NDE sensor systems is far from trivial. It requires a custom electronics development with some “out of the box” thinking. We cannot treat the hardware and software independent but need to design them jointly. In addition, it should be mentioned that hardware architectures in the NDE field are more demanding compared to others, e.g., due to requirements such as high voltages or high powers for ultrasound, for electromagnetic acoustic transducers (EMAT) or for X-Ray, respectively.
- The classical approach to designing sensors might not be the most suitable for the NDE4.0 vision, as it could waste a lot of potential regarding efficient data acquisition. Current sensors often have
a traditional design in terms of the geometry for spatial sensors (e.g. linear, rectangular, or circular arrays of equispaced sensor elements) or their approach to sampling time (like a sampling and hold stage in Analog-to-Digital Converters ADCs, which focusses on a very short period of time). For the NDE4.0 vision, a different mindset is needed. A most advanced measurement might require different temporal and spatial patterns than a classical Nyquist-based sensor.

- Another key feature for developing innovative sensors lies in their miniaturization. Here, current technology (such as the current piezoelectric transducers for ultrasound) might not scale well. There exist new approaches that have not been explored in the field of NDE yet, such as Micro-Electro-Mechanical Systems (MEMS) based technology based on Capacitive/Piezoelectric Micromachined Ultrasonic Transducers (CMUT/PMUT). Note that the miniaturization opens the potential for having a large number of spatial channels, which offers a significant amount of flexibility for spatial adaptation but also poses challenges in terms of the data rate, for which our NDE4.0 vision put forward in this paper (like sparse signal representation and auto-adaptive data reduction) can provide suitable solutions.

- Sensors should be equipped with the capability of self-checking and auto-calibration such that they become capable of delivering the expected signal quality by automatically updating their settings according to the current environmental and functional field. Self-checking is increasingly becoming necessary especially if the sensors are integrated in complex products and processes where they are required to perform autonomously. Thus, the self-checking capability is required to warn about any malfunction in the hardware. This is an essential feature for the cognitive behavior of an advanced sensor system of NDE4.0.

6.2.2. Challenges for Applied AI

Regarding the main challenges for applied AI we are foreseeing:

- Building big data sets for training AI (deep networks) on NDE data is required to unleash the full potential of deep neural networks in this field. In particular, we need to establish standardized benchmarks (real-world data as well as simulated data) in order to validate the accuracy of AI-based architectures on a common data set. As there are a growing number of tasks where a single modality cannot provide a sufficient evaluation, multimodal inspections are increasingly required. This poses additional challenges in terms of the data sets and benchmarks to cover their multi-modality and represent them in a unified data format.
Acceptance of AI in the NDE world: The acceptance will require the community to build trust in the AI. To this end, several aspects have to come together. Firstly, we need to be able to track and comprehend the AI’s decisions by means of understanding its reasoning. This is often referred to as explainable AI in the literature. Secondly, we need to ensure that the integrity of the data the AI is training on is secured to avoid potential manipulations of the training process. Thirdly, the electronics that the AI is running on need to be trustworthy as well. This is becoming a major research field in the electronics community, referred to as trusted computing.

Another crucial aspect is the AI’s power consumption. AI algorithms have surpassed humans for many challenging tasks, including the games of chess or Go, but also image classification and others. However, though performance is now often superhuman, this comes at the price of a significantly higher power consumption. If we restrict the AI to the same power a human brain uses, it can still not perform reasonably well. For the NDE field, power consumption can be an important issue, in particular if we want to integrate it on autonomous sensor platforms, powered by batteries or even renewable energy, which requires low-power operation modes. This is a moderate challenge if the sensor applies inference on a pretrained network only, it can become a serious obstacle if retraining on the fly such as in active learning should be applied on the sensor itself (i.e. in cases where it cannot transmit the data to a central unit carrying out the training). To tackle this problem, we need to consider scalable/lightweight AI where pruning methods are used to condense neural network structures to their essential part. Moreover and more importantly, novel hardware architectures that are tailored to the AI learning and inferencing process are required. One example lies in the concept of neuromorphic hardware architectures [78]. The long-term vision in this area is to bring AI on a chip via low-power-customized hardware/software components.

It would be worth adding, especially for complex inspection situations that NDE4.0 could benefit much more from AI in combination with physical understanding. For example for ultrasound inspection of objects that were previously uncontrollable this will allow for an increased quality of quantitative reconstruction of the product, taking into account further features like the irregular shape of the outer and inner surfaces, the anisotropy of the speed of sound or increased attenuation. To solve these tasks, the solution lies in using the modeling power of AI tools (mainly DL network) for learning the signal propagation in inhomogeneous and anisotropic media, to empower the reconstructions with AI-based approaches for reducing artifacts and perform on-the-fly reconstruction, for instance on graphics processing units (GPUs). The consideration of the physical
understanding for building appropriate AI models is a necessity in this field and allows a better understanding of the generated data.

6.2.3. Challenges for Secure Data Exchange

- In networked industries, not all data can be shared and not everyone will be willing to share all the data. At the same time, we may not trust the data we get from others, especially if our processing steps depend on data gathered in earlier processing stages of the same specimen. A potential solution is given by distributed storage technologies such as the blockchain [79] where data integrity is automatically maintained by virtue its design.
- Moreover, the abundance of digital data opens the path for new business models, e.g., internet-based services for data storage, data processing/analysis by human experts as well as AIs, data visualization, and many more. This requires further clarifications how to deal with data ownership and the digital right management. The Fraunhofer society is pursuing these aspects in the initiative International Data Spaces Association (IDSA) [https://www.internationaldataspaces.org].

6.2.4. Challenges for Standardization

In general, future concepts for standardization have to cope with the conflicts arising from the innovation speed of the digital transformation and the expectation of the NDE community for safe and trustworthy inspection systems. Of course, there are slightly contradicting requirements because of different philosophies established in the internet and digital communication technologies versus the classic NDT sub-disciplines like material science, construction engineering, electronics, machining technology, etc.

That is why new procedures for validation and standardization should be implemented for NDE4.0. We expect that standards will be driven by the power of international established business stakeholders as well as by new and non-classical technology companies or suppliers of data ecosystems for NDE4.0. Thus, static standards are going to be substituted by flexible procedures, which describe how innovative NDE systems must be validated to get approved and certified. This concerns the adoption of new digital technologies (AI, encryption technology, microelectronics, etc.) as well as training and qualification of personnel for NDE4.0 (data competency, new workflows, etc.). Because the provision and the exchange of data are the most essential element for NDE4.0, similar requirements for a flexible standardization procedure have to be realized considering aspects like data integrity, guaranteed data sovereignty and safety against data manipulation. Almost all of the national NDE communities and societies currently tackle all these issues. First international standardization and companion specifications are in progress.
6.2.5. **Outlook**

Overall, there are significant challenges to be addressed which require worldwide cooperation among researchers in the NDE community along-side the digital transformation of the industry and the society.

The long-term vision behind these endeavors should be to push the development of smart sensor systems toward human-similar sensor systems that can adapt themselves to new environments based on their experience and their observations and can learn to solve entirely new tasks using multimodal inputs. Such features are essential components of the behavior and capabilities of a truly cognitive sensor system.

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