A Versatile Sensor Data Processing Framework for Resource Technology

P. Kaever [a, b, *, 1], W. Oertel [b], A.D. Renno [a], P. Seidel [a], M. Meyer [a], S. Koenig [a, b], M. Reuter [a]

[a] Helmholtz-Zentrum Dresden-Rossendorf, Bautzner Landstr. 400, 01328 Dresden, Germany
[b] Hochschule für Technik und Wirtschaft Dresden, Friedrich-List-Platz 1, 101069 Dresden, Germany
[*] E-mail: p.kaever@hzdr.de

Abstract: Novel sensors with the ability to collect qualitatively new information offer the potential to improve experimental infrastructure and methods in the field of research technology. In order to get full access to this information, the entire range from detector readout data transfer over proper data and knowledge models up to complex application functions has to be covered. The extension of existing scientific instruments comprises the integration of diverse sensor information into existing hardware, based on the expansion of pivotal event schemes and data models. Due to its flexible approach, the proposed framework has the potential to integrate additional sensor types and offers migration capabilities to high-performance computing platforms. Two different implementation setups prove the flexibility of this approach, one extending the material analyzing capabilities of a secondary ion mass spectrometry device, the other implementing a functional prototype setup for the online analysis of recyclate. Both setups can be regarded as two complementary parts of a highly topical and ground-breaking unique scientific application field. The requirements and possibilities resulting from different hardware concepts on one hand and diverse application fields on the other hand are the basis for the development of a versatile software framework. In order to support complex and efficient application functions under heterogeneous and flexible technical conditions, a software technology is proposed that offers modular processing pipeline structures with internal and external data interfaces backed by a knowledge base with respective configuration and conclusion mechanisms.

Keywords: Secondary ion mass spectrometry, recyclate analysis, resource technology, hardware framework, multi-sensor system, processing pipeline, image processing

1. Introduction

Application fields like the online analysis of minerals or recyclate (OAMR) or the analysis of material composition on an isotope level using secondary ion mass spectrometry (SIMS) apply different analytical methods to understand the structure and composition of material samples. In many cases, the integration of additional sensors into the existing systems offers the potential for significant improvements of these methods. Using the OAMR example, a more comprehensive characterization of the probed material with improved analytical precision could be obtained by the use of a well-directed combination of diverse sensors, especially for highly complex, inhomogeneous samples [1], [2]. In the case of SIMS, additional components permit an increased resolution [3], [4]. While both fields use different equipment, they share the need to extract knowledge on high-dimensional sensor data. The functionality of processing, feature extraction and visualization of sensor data thus becomes a core element of the analytical method. In order to improve the significance of material analysis, a group of researchers from HZDR (Helmholtz Zentrum Dresden-Rossendorf) and HTWD (Hochschule für Technik und Wirtschaft Dresden) has set up a data processing framework with a structure that can process both slow control and data stream aspects for the diverse scenarios of SIMS and OAMR.

Extending the sensor hardware and processing functionality of the aforementioned multi-sensor systems raises several problems which need to be solved before a widespread use in industrial applications, especially in the field of mining and recycling, is possible. Both for SIMS and OAMR, the implementation of specific processing algorithms is poorly prepared by industrial manufacturers. High material throughputs in OAMR result in large data streams that request both fast data transfers and high processing capacity. Dedicated sensor setups for visual cameras come with well-known data structures and efficient algorithms; but only advanced co-registration of sensor features is able to improve performance. Accurate detection crucially depends on well-designed algorithms and data structures which are non-trivial in the case of a multi-sensor setup.

As implementation effort is a constant issue, the core idea is to arrange processing modules in a flexible component-based approach. Heterogeneity of applications creates the need for a flexible software extension; thus, the description of pivotal interfaces as well as data representations become a crucial part of the overall design. From a software-based point of view, this framework has to implement a data base for sensor measurements and a knowledge base comprising reference sensor data respectively the necessary background knowledge to process them. Scientific users have to build them up, step by step, by expert-guided acquisition processes or system-controlled learning processes.

2. Hardware Architecture and Application Background

The quality of extracted information depends to a large extend on the quality of sensor hardware. Sophisticated algorithms can make best use of new sensor types and may also be able to compensate the imperfections of analogue signals to the noise level, but only a proper selection of sensor hardware and the extraction of high-quality primary sensor information can really improve experimental results. Individual sensors require meticulous preparation of their physical environment to increase the signal/noise ratio. Integrating new sensors may lead to a close coupling to existing infrastructure (e.g. when extending a SIMS). Another outcome may be the definition of an entirely new processing platform as in the case of the OAMR [5].

In both cases, sensor infrastructures have to be interfaced to different subsystems in experimental hardware with regard to triggering and clocking, slow control and data streaming (for complex sensors) [7], [8], [9], [10]. These subsystems can be considered as being extensively independent. Clocking and trigger schemes belong to the critical components in scientific instruments as they directly define the quality of analogue data sampling. They depend on the physical process to an extent that no generic scheme may be applied. With respect to sensors, slow control includes calibration and setting functions providing all the essential preconditions for data acquisition. The aspect of data streams becomes relevant for sensors with high sampling rate, often in combination with high analogue resolution and channel count. In the following subsections, we will detail these aspects using two experimental facilities from the OAMR and SIMS environment.

Hardware equipment for OAMR *by SenSys*

Recently, the SenSys system [5] has been set up as a multi-sensor system based on optical spectroscopy for material flow analysis at the Helmholtz Institute Freiberg for Resource Technology at HZDR (fig. 1). The mechanical hardware of SenSys consists of a conveyor belt on which the sample material is placed. Conveyed samples are scanned by different imaging sensors mounted above the belt and establishing different sensor sections which have to be merged. Once the material has been scanned, it runs into a collector box at the end of the conveyor belt. This setup allows for quasi-continuous operation with the belt running at speeds between 0.05 and 1 m/s.

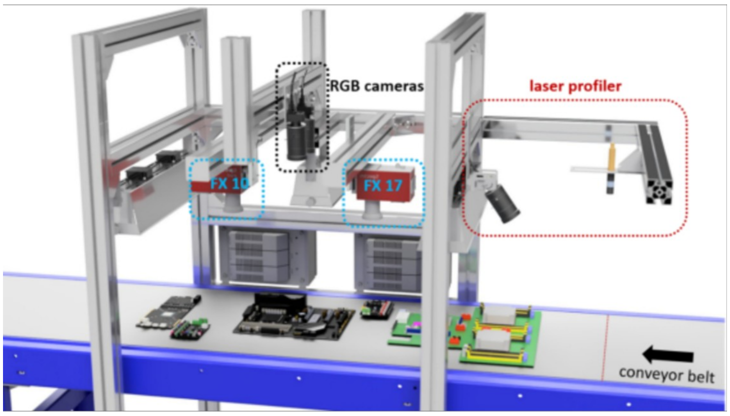

Figure 1: Schematic view of the SenSys hardware components.

The employed sensors can be divided into three groups based on their working principle. To detect the height of the individual objects, a laser profiler, consisting of a line-excitation laser (633 nm) and an RGB camera (Teledyne Dalsa Nano C4030), is used as first sensor unit. The angle between camera and laser line is set to 30°, the camera achieving a height resolution of ca. 0.4 mm. Two similar fast industry color cameras (Teledyne Dalsa Nano C4020) provide a high spatial resolution and can be combined together to create a stereoscopic image of the probed scene. Each of both cameras acquires a full frame at once. In addition, two different cameras are employed for spectral imaging of the material reflectance in a wavelength range of 400-1000 nm (Specim FX 10) and 950-1700 nm (Specim FX 17) working as push-broom scanners acquiring the data line-wise, generating a total data stream of 500 MiB/s in the present setup.
Testing geological samples such as drill cores and rock pieces and also waste materials out of metal scrap or printed circuit boards (PCB), the performance of the data integration proved to be a powerful tool for carrying out scientific studies with the SenSys system.
Sensor fusion in this system is equivalent to a coherent geometric mapping of different sensors into a joined data model for further processing. Coherent stationary geometric calibration of all sensors involved is the first indispensable step. For moving objects, isometric triggering offers an efficient scheme for the mapping of both line- and 2D-cameras into a common data model. As most optical sensors provide a trigger interface, the design of a module that delivers isometric triggers was a key requirement.
In the case of SenSys, isometric camera triggering has been implemented using a microcontroller-based approach, delivering a belt position sampling rate of 250 kHz which leads to a special resolution of 12 micrometres at 3 m/s belt speed. Based on this signal, several trigger groups with fixed dividing frequency to the belt position increments may be defined and forwarded to the respective cameras. This proves sufficient in comparison to camera resolution and exposure time. In both cases, clocking schemes are the basis for high quality data acquisition, being configured (but not directly interfaced) via the control system.

Material structure investigation by enhancing a conventional SIMS

The analysis of the chemical composition of solids using a dynamical SIMS system [3] is essentially based on the mass spectrometric analysis of sputtered material. For this purpose, a fine-focused primary ion beam scans a precisely defined area of the sample surface. The ionic fraction of the sputtered material is transferred to the mass spectrometer via an elaborated ion optical system. Mass-separated ions are then measured using Faraday cups or electron multipliers within a commercial CAMECA 7fAuto instrument; for sputtered volume determination, a white-light interferometer Contour GT-K (Bruker) has been used. The SuperSIMS developed at the HZDR represents a further development of this basic concept [4]. Here, only the negative mass-separated secondary ions are injected into a tandem accelerator via a new unit of ion-optical modules. Specific processes inside this accelerator lead to the complete destruction of all molecular ions and thus to the reversal of the polarity of negative ions at the terminal. As a result, molecular interferences no longer occur in the subsequent analysis in the high-energy mass spectrometer, and the detection limit can be improved by several orders of magnitude compared to a normal SIMS analysis. As a consequence of redirecting secondary ions to detectors that are SIMS-external, the integration of accelerator and detector hardware plus ion-optical sections as described in Fig. 2 prove to be critical for such an enhanced instrument. Eventually this has to be enhanced by extensive analytical and image generation software.

Consistent control can only be provided by a master control interfacing the different complex components which include embedded control units, accessing the data of all relevant sensors (Faraday cup, electron multiplier, image sensor) and actors (SIMS, accelerator, ion optic magnets, etc.). Typically, clocking schemes provide hardware synchronisation with low jitter; inside a SIMS, the detector clock thus has to be derived from the primary ion beam sampling hardware on the probe. Slow control and data stream interfaces are far more complex and require sophisticated techniques for consistent processing - both on system and component level [8], [9], [11], [12].

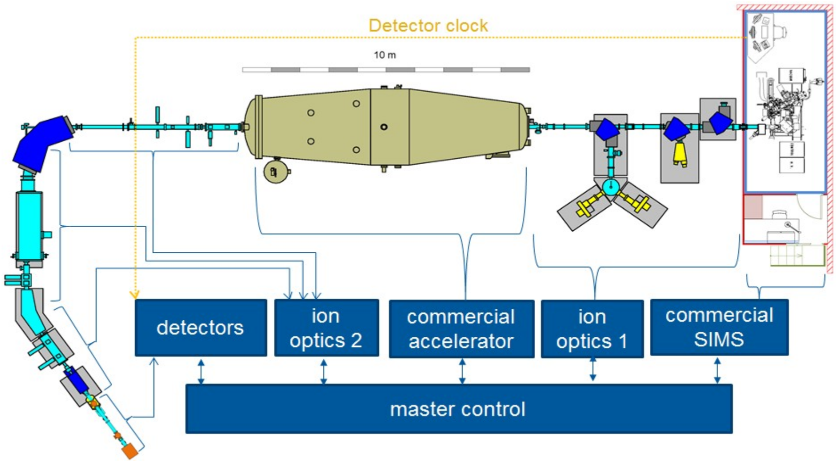

Figure 2: Schematic view of SuperSIMS hardware components.

Extending commercial SIMS equipment with new evaluation methods touches the core of software architecture inside such an instrument. Under the granting of access to the source code, a minimally invasive approach was the implementation of a service for the distribution of raw sensor data. This allows both the preservation of the original functionality and the implementation of additional interfaces with minimum processing load. Among different slow control systems, the experimental physics and industrial control systems (EPICS) was chosen as integration platform as it allows a representation of complex subsystems (commercial SIMS, commercial accelerator and detectors) [8], [9], [12]. EPICS contains a set of software tools and applications to build up a distributed control system using dedicated network protocols called Channel Access (CA) and pvAccess (PV) realising a client/server relationship and publish/subscribe techniques for I/O-related communication. Input/output controllers (IOC) represent the device layer that connects directly to physical I/O. EPICS is open source and used in many research facilities world-wide [8] [13]; hence, many software modules and libraries on different implementation levels are available; e.g. for graphical user interfaces, storing and accessing historical data plus IOC for particular PLC types and communication protocols like Modbus.

In order to integrate the existing SIMS into the EPICS control framework, its control was extended by dedicated IOCs which perform I/O-operations. It is divided between two computers - one performing realtime-tasks and another for processing and visualization. Fig. 3 shows the overview of the SIMS control with the EPICS-IOC-extension. IOC-extensions have been implemented on the visualization PC without interfering with the manufacturer's software or compromising realtime-performance. EPICS IOS's are suited to interface IO-data from the machine. Their data layout is defined by structures and enumerations that can be used to separate and convert the data into EPICS process variables and parameters. Consequently, this interface may cover the range of slow control data and prepares the setup of a master control.

Developing IOCs as I/O-proxies for components along the SuperSIMS beamline creates a flexible approach which consistently links data from different hardware sections into a common data base and will result in a homogeneous control system. This starts with the commercial SIMS, it will include the accelerator and extend to new detector hardware or ion-optics beamline segments. EPICS thus allows to control the SuperSIMS both manually and with the support of automation logic, e.g., it provides a framework which is able to incorporate machine safety and setup functionality.

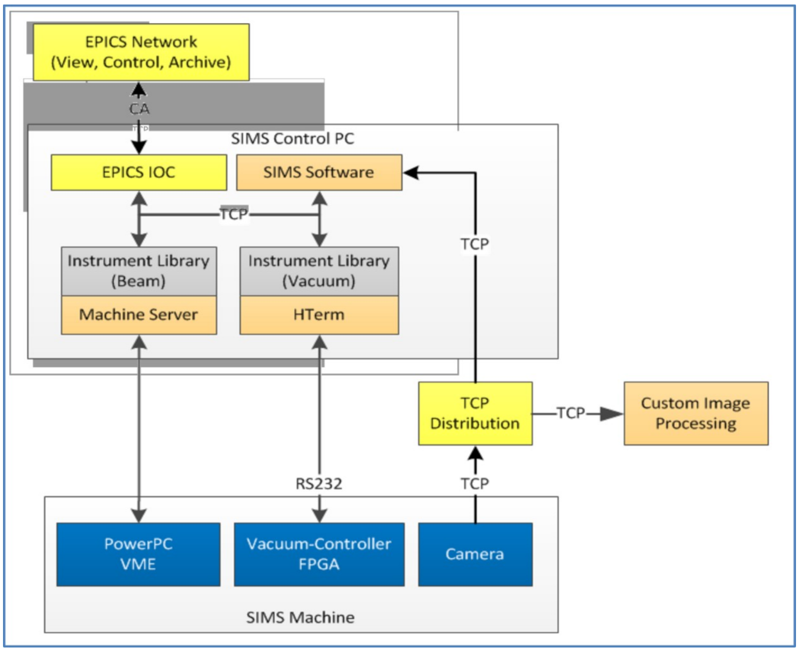

Figure 3: Overview of the SIMS interfaces.

As EPICS has a focus on slow control, data streams which have to undergo elaborate processing have been handled separately. Image data streams from the SIMS detectors were interfaced applying a distinct proxy server that has been placed between the realtime-computer and the visualization PC. The proxy-server listens on the original network port, transferring the raw images from the SIMS machine to every connected peer for further processing. This preserves the functionality of the original software and pushes image data into the pipeline for analytical processing.

Although SuperSIMS and SenSys differ in equipment and application, the general architecture of a hardware layer with inherent trigger schemes, slow control and data stream interface to a processing layer is quite identical, thus motivating a generic software approach for scientific data analysis.

3. Software Concept

Generic system architecture

The basic principles of the software system necessary to support the tasks of the two aimed application categories as well as to integrate the data coming from different sensors or going to different actors were developed in [6]. The corresponding ASARBWG project at HTWD targeted a pilot system for hardware integration and software development especially for the SuperSIMS and SenSys installations. There, a vertical three-layer software architecture was proposed. The central, conceptual layer defines unified global data and program structures. Internal and external layers refer to different efficient implementations and user interfaces, respectively. The conceptual layer with its software components and relations is shown in Fig. 4. It contains horizontally three major subsystems.

On the left, the real states and processes of the application equipment with their sensors and actors are directly connected to acquisition components to deliver raw data as input to the system. Vice versa, control components allow setting selected output parameters. Raw data can immediately be used online or may be saved by a storage component as file data for later retrieval and offline use. Depending on the context, it is fused and organised in sensor- or actor-specific formats [14], [15].

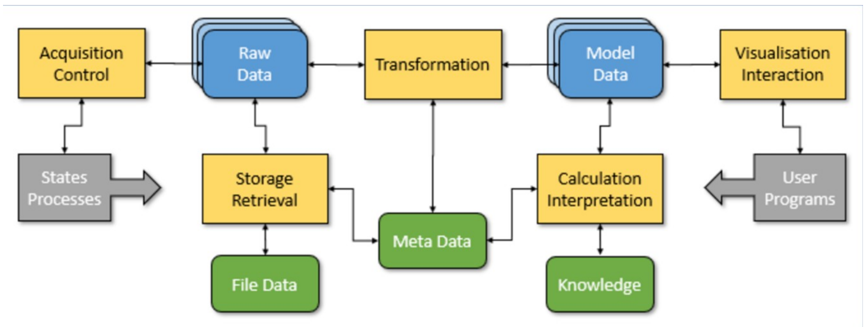

Fig. 4: Conceptual software system structure.

On the right, users and other programs get information out of the system by visualisation components and influence it back by interaction components. Both kinds of components do not work on raw data directly, but on model data that abstract from concrete sensor and actor features as well as file formats. Model data is organised along common formats and unified contexts. They are also source and sink of calculation and interpretation components that use domain knowledge to compute additional values or derive new conclusions [16].

The connection between raw data and model data in both directions is provided by a set of transformation components guided by metadata. Metadata is generally relevant for the definition of structures and meanings of data used in the system.

On the internal layer, the whole system is implemented in C/C++ using OpenCV for processing two- or three-dimensional image and regular data as well as VTK for processing and visualizing multidimensional and structured data. For performance reasons, on internal layer, OpenGL and an OpenCL-based approach [17] are involved. The operating system is MS Windows for current development and Linux Ubuntu for later

process integration. On the external layer, a window- and a web-based user interface provide access to the most important components of the system.
This three-layer architecture, especially the introduction of the unified conceptual layer, has led to an enhanced transparency of the entire system and a substantial reduction of the development and integration time for new software components which is essential for an experimental system.

Pipeline structure
Because most of the data processing tasks in the developed system are considerable complex, they are subdivided step by step in single operations and organised as pipelines with flexible ordered or half-ordered activation structures. The result is a multiple pipeline system [18], [19].
In such a pipeline, input data taken from a raw or model data container are computed by pre-processing into prepared data as input for the content-dependent kernel transformation process. At the end, the resulting transformed data is post-processed and put back again as output data into a proper raw or model data container.
The transformation itself consists of a sequence of single operations guided by metadata and knowledge to fulfil the intended task. The most important pipeline of image processing consists of the steps feature extraction, region estimation, object detection and scene evaluation. Another typical pipeline is data visualisation with the steps filtering, mapping and rendering. Finally, problem solving pipelines apply different mathematical functions, logical formula sets or rule packages in order to get conclusions by respective inferences.
On the external layer, each pipeline has a graphical representation on the user interface. Here, the operations, their parameters and their activation relations can be monitored or changed interactively [20]. In this way, pipelines may also be defined by non-developers. Fig. 5 shows an example pipeline on the web-based user interface where video-stream image matrices are shown to be processed by a background separator; later the mask and the foreground image are conjuncted and displayed in addition to the mask image.

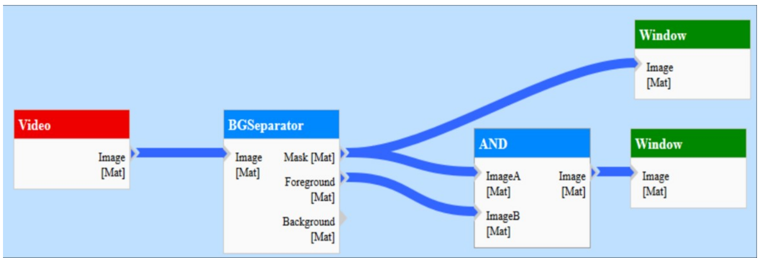

Figure 5: Visualized example pipeline.

On the internal layer, operations can be realised using the multi-threading capability of several main processors and cores or involving the massive parallelism of the graphics boards. This is done manually by the programmer, but more and more automatically by the image processing and visualisation libraries. The result is higher processing speed and resource utilisation [21].
Using a generic and flexible pipeline structure allows to implement basic forms of quite different - in previous systems separately realized - application components as single pipelines in one system: image acquisition, process supervision, spatial count analysis, profilometer viewing, knowledge-based classification, example-based learning, stereo recognition, laser light section, structured light profiling and hyperspectral viewing [22], [23], [24], [25], [26], [27], [28].

Data structure

Raw data is generated by the acquisition and control component and processed further on by transformation operations. In parallel, they can be stored in files and retrieved back from there. The structure of the raw data is characterised by their location in the overall system near the sensor input, respectively actor output. So, the data has to conserve the specific authentic set of original measure or control values. At the same time, it is stored in generic containers allowing certain generic operations to handle them. These two requirements are realised by organising the data in the form of an ordered vector of measure control frames in the container stream data (see fig. 6). A measure control frame is a data element with channel identifier, time stamp, space position and real data values. The role of the data values is described in the channel-information operating as data header.

Using this raw data structure, image and video data produced by camera sensors in standardised formats can be managed just as vector data produced by any of the intensity or counting sensors in particular formats. Actor data is defined accordingly.

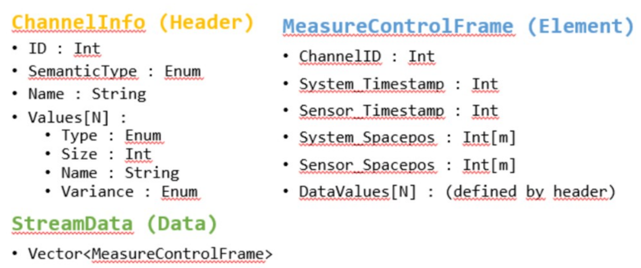

Figure 6: Sensor data format at input.

Processing pipelines carry out complex synthesis or analysis operations. For that, they require a set of unified data structures as formatted operands and interfaces for all input, output, processing, storage, retrieval, calculation, interpretation, visualization and interaction tasks. These model data structures are formed by multi-dimensional spatial or linked graph structures organised in temporal sequences and attached by textual attribute vectors. Meta data describe the syntax and the semantics of these data.

All unified data together provide the essential basis for the required flexibility, changeability and practicality of the proposed multiple pipeline system.

Flow structure

The task of the entire system can only be fulfilled efficiently if they are distributed to several cooperating components. Therefore, it is necessary that involved sensors, actors and computers are integrated with each other by a network. The essential subtask is to organise the data and the control flow among them by proper interfaces. Fig. 7 contains a schematic representation of this flow.

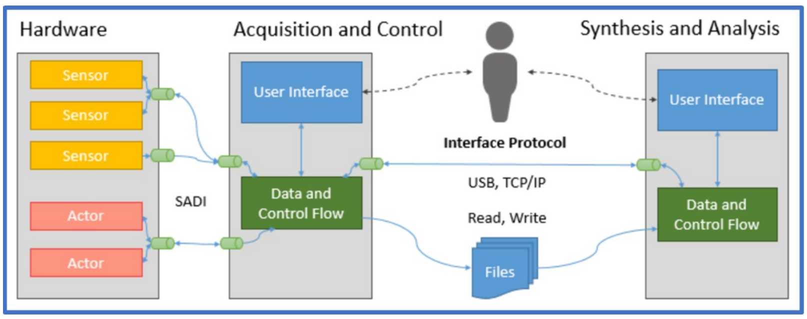

Figure 7: Data and control flow.

All sensors and actors are attached by a sensor-actor-data interface (SADI). It contains externally generated measure data like quantity vectors, image matrices or sensor parameters as well as internally generated control data like event requests, event responses or actor parameters together with precise time stamps. The conversion of specific raw sensor and actor data is implemented either on hardware driver level or system software level. The data transfer between processing units is handled by a client-server architecture, using either the TCP/IP or the USB protocol. All the cameras are integrated by Gigabit-Ethernet as in [29]. For offline work, the data-exchange is also possible via read and write operations on files. This dataflow may be monitored by user interfaces.

The performance of the entire system depends on many factors: frame sizes, frame rates and number of the sensors, processing times and number of the computers, data transfer times of the network, runtimes of the evaluation algorithms as well as structures and number of data and knowledge elements. In our development environment at HTWD, we observed cycle times for the different pipelines between 0.1 and 10.0 s, whereas the lower limit is determined mainly by the network band width and camera frame sizes, the upper boundary results from the combination of frame sizes and transformation algorithms.

4. Experimental Results

While the pipelined module structure described above is able to handle both SuperSIMS and SenSys applications both systems differ in data rate and processing complexity. SuperSIMS provides data at much lower rate while the probed material is sputtered, creating a depth profile of the scanned region with a multitude of different elements inside the sputtered volume. Conversely, the multi-sensor system SenSys at HIF generates much higher data rates by scanning the surface of moving samples with different cameras simultaneously; each giving a defined spectral range and preferably planar regionalization.

Both systems benefit from the presented data processing pipeline by enabling real-time data streaming and full sensor control. Hardware-related issues have been addressed by dedicated interface modules, creating direct access to raw images without modification of proprietary firmware. Thus, after establishing the source for data streaming, we can handle the streamed data according to our needs and develop flexible, customised solutions for image transformation such as distortion correction, image stacking and white-balancing. Moreover, the innovative design of the system software is capable to incorporate diverse analysis tools. This is a great advantage compared to current embedded firmware which can be modified to incorporate new sensors or functionalities only with large effort.

Our hardware integration modules and the package of software routines overcome these obstacles and will be continuously further developed to meet future tasks, e.g. the incorporation of new sensors or image classification methods.

Experimental results at SIMS material analysis

Several pipeline-based programs are designed for the use in the SuperSIMS environment. They are already in practical use and deliver helpful information for operators and users. A dedicated software module receives raw images from a commercial SIMS during the scanning process and stores these data in an open and lossless file format (*.pgm). As raw-data-transformations operate on individual sensor data, their processing time has been improved by multithreaded implementations for multi-core-processors or GPU-mapping.

A spatial count analyser system processes the data collected by the image receiver. It interpolates counts in a volume size using a three-dimensional kernel and a marching cube algorithm for iso-surface detection. Alternatively, a volume renderer uses semi-transparent voxels and allows viewing the inside of an object. Offline 3D-volume processing is performed by reading a series of files collected by the image receiver; each representing a thin layer of material. The resulting volumes can be used to extract a 3D-surface defined by iso-detection levels of different isotopes. This allows visualizing the 3D-shape of any contained substructures clearly. To look inside an object, the visualisation can be switched to be semi-transparent (fig. 8 left image).

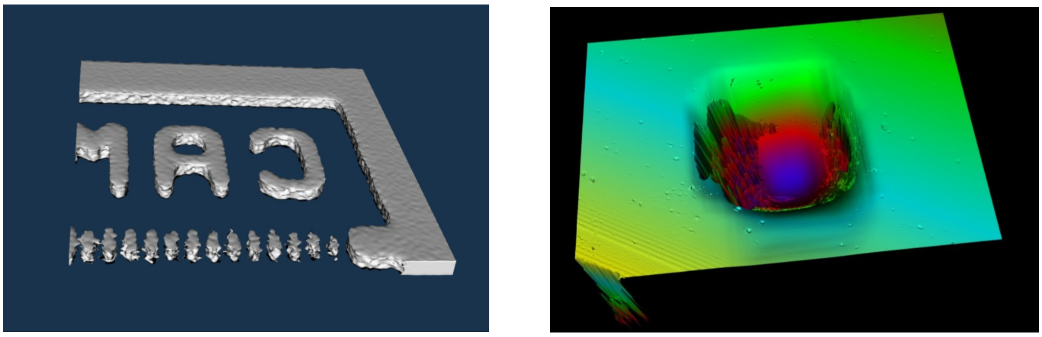

Figure 8: Example results for spatial count analyser (left image) and profilometer viewer (right image).

Shape and volume of the real sputtered area can be inspected with the use of a Contour GT-K white-light interferometer. This unit transfers its data into a dedicated viewer system by ASC formatted files. In the viewer system, a three-dimensional surface of a sputtered material object is computed. The result can be examined from a scientific point of view with different camera points, camera perspectives, space resolutions and color mappings. A typical example for the viewer system output is the colored height profile in fig. 8 right.
Out of various analytical methods in dynamic SIMS instruments, the one which places the highest demands on the internal synchronisation inside the instrument is the measurement of the three-dimensional distribution of different elements in a precisely defined scanned area of the sample. In order to evaluate the processing of large amounts of data representing this three-dimensional distribution, e.g. in a natural mineral, measurement data were taken in the normal SIMS mode, not in the much slower Super-SIMS mode. As the data structures are identical, this approach enables the validation of the data processing pipeline. First reference tests were made on regular structures which are provided for calibration purposes. The structures are manufactured by deposition of thin tantalum layers on Si wafers. In this case, the distribution of the isotope ^{181}Ta and the molecule ^{29}Si^{30}Si were measured. The measurement of the element distribution in natural minerals is much more demanding. In addition to a large number of elements/isotopes to be measured, these are also determined at different measuring times. This corresponds to different sputtering depths in the respective mineral.
The spatial and temporal integration of sensor signals is obligatory as the process of sputtering the material sample by ion beams needs a precise spatial calibration and temporal synchronisation of all participating agents. Thus, the time of arrival of material particles must be linked to the time of sputtering on the sample because this gives the information about their former location in the material sample. At the same time, the arrival time contains information about the chemical substance because of the mass, and hence, acceleration and resulting velocity of the particles. Before and after the regular measurement, the particle flow intensity of the primary ion beam is determined as

reference value. The measurement of the sample itself is done with a spatial resolution of up to 512x512 dots in an 80 ns time grid. The resulting particle intensities vary between 1 million and 1 billion per second. Fig. 9 illustrates the relationships between the sputtering time path, the sample spatial grid and the global camera image.

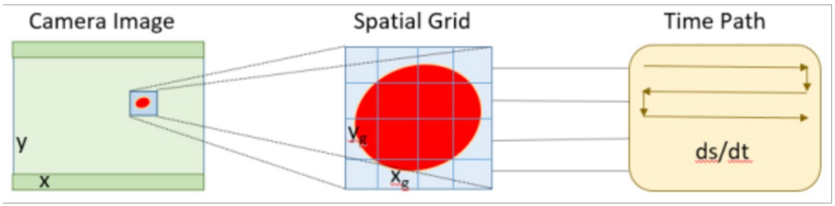

Figure 9: Image-space-time synchronisation in SuperSIMS.

All experimental tests prove the applicability of the developed methods and demonstrate functionality and flexibility of the approach chosen here.
Compared to other methods of evaluating and using 3D imaging data from dynamic SIMS measurements [34-36], there are several advantages.
The automatable detection of different matrices in the sputtered volume, combined with the reconstruction of the shape and volume, allows the automatic quantification of element and isotope concentrations based on the availability of matrix-matched standards. This is currently only possible for measurements in exactly one matrix (e.g. [34]) otherwise the element or isotope ratios are presented. The correlative automated analysis of the 3D image information of the SIMS - signal and the signal of the white-light interferometer allows the automated determination of the sputter rate and the analyzed volumes of the individual phases. This principle makes use of additional sensors; it leads to improved analytical results and can be transferred to all other methods of correlative microscopy of SIMS measurements [e.g. 37].

Experimental results for material flow analysis
Using the setup of multi-sensor systems at HZDR, different material streams, especially with the focus on drill cores and secondary resources (e.g. printed circuit boards and metal waste) have been monitored. Besides providing classification algorithms, this work resulted in two important, innovative tools for the online material stream characterization: the automated object height detection by laser profiling and the streaming and pre-processing of RGB color and hyperspectral reflectance images.
Laser light section bases on a monochrome camera together with a wavelength filter and an active line laser. The software determines the deviation of a straight laser line in the camera image, using triangulation to calculate the height. This approach proved to be superior to stereo camera triangulation with respect to computational burden, resolution and ruggedness. Applying it to a scene on a conveyor belt, a complete three-dimensional surface profile (2.5D) of the moving objects in a rectangular area can be derived in real time. Exemplary, in Fig. 10 two images of a reconstructed PCB are shown visualizing both the preliminary height map (left) and the final 2.5D image after incorporation of the greyscale reflectance and a rendering step (right). The detailed object reconstruction will be further used as a base map on which the hyperspectral reflectance data projected using the co-registration approach of the synchronously triggered image acquisition for both hyperspectral cameras.

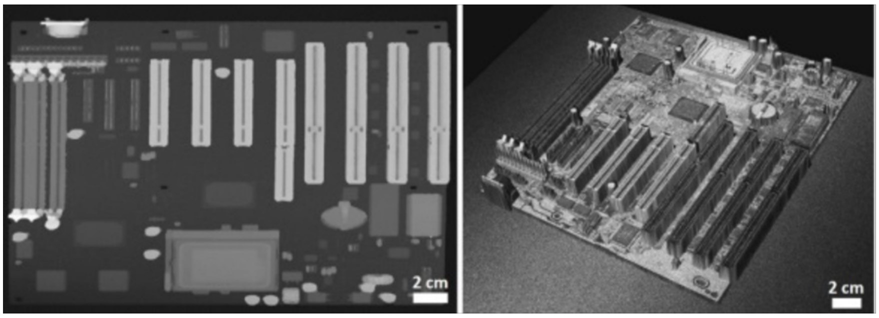

Figure 10: 2.5D-reconstructed images of the laser profiler for a PCB sample. Height map depicted in grey scale with distortions in x-y directions being still uncorrected (left). Rendered 2.5D image of the sample taking the greyscale values of the laser reflectance and the height information into account (right).

One of the major tasks was the integration of multiple Gigabit-Ethernet cameras with regard to configuration and image transfer. For example, hyperspectral (HS) cameras were interfaced and their data streams have been recorded in the aforementioned pgm-format with full resolution. Presently, the image streams of five cameras are processed and stored which results in a data flow of 500 MB/s. The configuration part covers parameters like capture regions, frame rates, trigger modes, exposure and overall capture times plus gain values for image sensors and pixel bit depths. In-built raw data transformations perform the change of image format, geometry and color. Raw color images may be de-bayered to get RGB information or compensated for uneven spectral light distribution and spotlights with a white balance algorithm.
Knowledge-based classification is based on camera sequence data and stored explicit knowledge about elements and their relationships located on pieces of electronic circuit boards. It contains image-processing steps like feature extraction, region segmentation and object detection on the basis of typical object parameters like color, saturation, intensity, texture, size or shape, allowing to specify their ranges or limits in dedicated tables for further optimization. Typical detection rates vary between 50 and 80 %. It is expected that the importance of this component will grow in future by collecting the amount of real expert knowledge, also to support the other detection components.
Example-based classification uses a manually prepared set of reference images, representing typical backgrounds, negative and positive training objects, representing typical scene elements. On the base of color images, a mask extractor generates a large number of assessed cropped image parts, using a multi-step cascade filter for later object matching. Analysing material flows, the comparison of the high-resolution RGB image with other hyperspectral reflectance sensor data has shown good results in feature extraction of co-located extracted areas [5].
Another example of the current object detection algorithms being fed by synchronous multi-camera data acquisition is the identification of PCB components with convolutional neural networks (CNN) (Fig. 11). We applied the VGG-16 network architecture [24] used for this task. While the network performs poorly in the detection of objects and in setting the correct bounding boxes using RGB images only, we obtain an increase in accuracy by taking information from the hyperspectral reflectance image into account [30]. This method is inspired by the region-proposal by guided anchoring [31]. The output of the supervised pixel-wise classification of the HS data is used to populate a probability map, which exhibits high values where the given classes should be located. This probability map is used along with the region proposal network of the CNN for the anchor localization, i.e. to set the box where an object from a specific class should be detected. The boxes with different grey scale color represent different object classes recognized by the network in a PCB image.

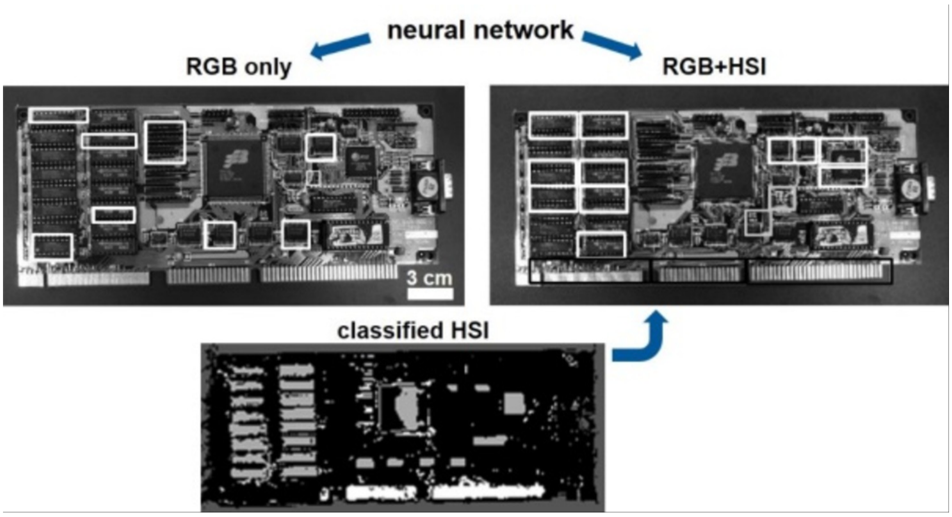

Figure 11: Comparison of the object detection of PCB components by a neural network using RGB images only (upper left) and RGB images combined with anchoring points from the classified hyperspectral reflectance image (upper right). White boxes mark the recognition of integrated circuits, grey boxes metal sheets and black boxes gold connectors. Different grey values in the classified HS image represent the different detected classes (lower image).

Our approach improved the mean average precision from 0.45 to 0.61 and reduced the inference time from 0.75 s to 0.32 s. Acquiring more experimental data for learning and improving the network architecture should increase the accuracy of the object detection and its ability to recognize a higher variety of object classes in the images.
The findings from the neural network dealing with different sensor data are promising starting points for a further investigation of the fusion of spectral data from different sources. Compared to other studies, where the fusion of RGB and hyperspectral reflectance was examined [32] [33], our network is able to deal with a limited number of training set and is better tailored for the application in PCB recycling. The inference times are shorter due to the compression of the hyperspectral data into a low-dimensional feature map. Moreover, the developed flexible software and hardware architectures enable an easier and more problem-adapted integration of further sensors, which is more challenging for the aforementioned other approaches. In addition, the ability of the here presented pipeline for streaming large data sets provides a unique opportunity for the further step of real-time multi-class object detection in material streams.

5. Conclusion and Outlook

The paper described a sensor data processing framework which has been applied in different hardware setups in the field of resource technology, ranging from secondary-ion-mass-spectrometry to optical image processing for recyclate analysis. Interfacing the existing hardware was inevitable groundwork to prepare the definition of new data structures and processing pipelines. The use of additional sensors could thus be implemented and tested on three different research and development facilities at HZDR and HTWD, yielding improved analytical results compared to the original setups.
For a large set of equal or similar features, open source libraries could be used. The present implementation allows the acquisition of raw sensor data in real time, sensor fusion in a common reference system and the flexible extraction of data on different processing levels for developers, experts and users.

This configurable processing pipeline framework serves as a base for further test and use scenarios, extending the systems application-specific knowledge-base. Future work aims at increasing sensitivity by integrating further sensor hardware. Extending model data and knowledge structures will also improve conclusion and learning processes, resulting in better material classification.

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