A Modular Sensor Fusion Approach for Agricultural Machines

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Summary
Today’s architectures for sensor data handling in agricultural equipment are static and single vehicle-centric. This means that they assume a static system configuration over time while ignoring data contributed by other sources like implements and other machines that they currently interact with. Therefore, it can be stated that the inability to adapt to machine reconfiguration can be identified as a significant bottleneck. The approach presented in this paper is designed to overcome this shortcoming. For this purpose, a data handling system was designed that combines solutions for management of distributed knowledge and data fusion algorithms especially designed for the demanding application field at hand. Besides supporting the user, this modular approach enables engineers to design future systems in a holistic manner with reduced complexity. Furthermore it can help to reduce hardware costs due to elimination of redundant sensing systems and pushes the limit of applications to open up new opportunities in the future.

Key words: modular architecture, sensor fusion, reconfiguration, vehicle state estimation

Introduction

In the field of agricultural machinery a trend towards an increasing degree of automation and documentation systems, as well as a strong desire for semi- or fully autonomous equipment operation can be observed. As a result of this, the complexity and level of sophistication of the manufactured machines dramatically increases. This is especially visible in the context of sensing capabilities that are added and extended today beyond the faintest ideas of engineers less than a decade ago. A good example for such a complex system is optical object/environment perception used for e.g. machine safeguarding or increased productivity (cutting edge detection, grain cart detection in forage and combine harvester operations).

Due to the broad spectrum of such applications, a very diverse market segment has formed that includes a wide selection of systems by the equipment manufacturers as well as a multitude of third-party implementers that typically fill niche markets. Based on the historically evolved system design processes, most subsystems are specified in a more or less isolated manner. In practical terms this means that an electronic control unit (ECU) is typically hard wired to one or multiple sensors that gather the information needed for the task to be pursued (see Figure 1). This fact is part of a strategy that allows manufacturers to reuse components on different platforms with only modest modification. Due to the fact that such a self-contained approach is pursued there is very little communication among the subsystems on a global (machine wide) level. Another consequence of the above approach is that data might have to be acquired multiple times using different sensing systems. Besides the increased costs this approach yields further unfavorable aspects. One of the major ones is information ambiguity that can lead to inconsistency problems.
Good examples of such challenges are yield measurement systems. Here different subsystems on a machine will provide differing results for e.g. the totally processed area due to different pieces of evidence employed as inputs to these systems. As an example a system that bases its information solely on the GPS-speed usually will provide significantly different total numbers than a wheel-speed-based approach. This is because of different measurement principles, update rates and vulnerability to external distortions like wheel slip or loss of satellite signal.

Figure 1: Standard Electronic setup on an ISO11783 system

As exemplified a significant architecture gap can be identified within a single machine, between machine/implement and diagnostics tools and in the communication between a machine and another physical entity like an implement or another machine. The latter scenario is quite common in agricultural processes like corn or grass harvest. As will be shown in the following section the architecture reflects a major bottleneck in the attempt to enrich the functionality and increase the degree of automation.

The impact experienced today will become even more eminent in the future since the number and level of sophistication of the machine’s sensing capabilities will dramatically increase. However, if the architecture is not geared for such smart sensing systems a lot of potential (and thus benefit) cannot be utilized. More than that, even the data flow design process of future machine generations will become more and more tedious since the system complexity will grow exponentially with each new device added. This will become even more of a problem when the industry tries to tackle the next steps towards the long term goal of autonomous machines.

Motivation

As opposed to other, closely related fields like e.g. the automotive industry, data handling architectures that assume a static system configuration over the product lifetime do not fulfill the requirements imposed by agricultural applications. This is because this domain bears some unique characteristics. Not only do the machine and implement combinations change quite frequently due to different tasks to be pursued but also the number of manufacturers that produce those implements, sensor and auxiliary retrofit subsystems is quite large. Therefore, the number of possible different combinations is incredibly high and beyond capacities to hard-code the respective structures into the sensor data handling system.
Thus, it is only a logical consequence of the above findings that the architecture should map such usage patterns to the way the system acquires and processes information. An example concerning the most common forms of reconfiguration is the addition or exchange of an implement or auxiliary sensor systems like e.g. GPS receivers. In order to get a better understanding of what such a process might look like, let us take a look at the following fictitious example:

Consider a usual work day on a modern farm as it can be typically found in almost everywhere. As the farmer studies the weather forecast in the morning he is pleased to read about clear skies and low winds. Hence, he decides to hook up a red sprayer to one of his green tractors to deploy some herbicide in one of his fields. Since the GPS system he bought a while ago is used by one of his employees he has to rely on the installed ground speed radar sensor as source of the vehicle velocity required for the documentation of his work. While time goes by the winds grow stronger. Therefore, our farmer decides to head back to his machine shed to park the sprayer and hook up a blue tillage implement to do some soil cultivation on another field instead. Meanwhile the RTK-grade GPS receiver is no longer needed elsewhere so he can install it on his tractor to be able to use his automatic steering system. In the early afternoon he is done with plowing the field and returns to his farmstead. As he feeds the data gathered into his desktop software he realizes that one of his smaller fields is due for the application of fertilizer. Thus, he heads back to his tractor and hooks up a yellow spreader to get the job done. After a hard day’s work he sits in his office to get the paperwork done. As he goes over the numbers of the day he realizes that the results of his PC software and the display in his tractor cab do not match.

Even though this little example provides a rather compressed view on reality it nevertheless underlines a few facts that one needs to consider when designing a data acquisition and processing architecture for agricultural machines:

- During daily operations a multitude of equipment of different manufacturers is typically combined in one farm operation. An architecture needs to live up to that and provide elegant solutions for the challenges that arise w.r.t. interoperability of equipment.

- The machine configuration changes quite frequently (sometimes even several times during one day). Therefore, the architecture needs to be able to deal with these dynamical aspects in the system without significant reconfiguration overhead.

- The tasks that can be typically found in a farming operation have fundamentally different characteristics. Hence, information needs to be interpreted specifically in this context in order to receive optimal results.

- The machine and the respective implements form a unit and become one single system for a given period of time. The same should apply to the data streams produced by sensing equipment.

- The lack of general data visibility and accessibility across system borders throughout the machine result in inconsistencies in data basis. In order to receive reliable results this needs to change.

The above points can be understood as a catalogue of the shortcomings that one experiences in current architectures. More than that, it should be used as a guideline in the design process for a...
next-generation data management solution that eases the data handling in multicolour fleets, increases reliability and quality of the sensor data, performs context specific data processing and enables new opportunities in the field of agricultural vehicles.

State-of-the-Art

The most prominent aspects where the shortcomings of the state-of-the-art can be experienced today is the area of telematics and documentation systems that are offered by a variety of manufacturers. The fact that only those two fields are named here does not reduce the magnificence of this problem but is rather due to the fact that other, more fundamental applications like e.g. subsystems for task automation and other control processes that suffer from this are not directly visible to the user. For these reasons the following lines will focus on the two aspects pointed out above.

Modern telematics and documentation solutions are designed to be vehicle centric in a sense that they focus on just the vehicle they are installed on. The way this is usually realized is by individually logging data on the machine’s CAN bus that is then averaged over a period of time (typically 30 seconds to a few minutes). Since there are several options of what sensor readings to use for e.g. ground speed or provided engine torque (and data fusion is usually omitted), it is up to the designer to choose which piece of evidence is used as a data basis for the system and which to discard. In the next step the averaged data is fed into a static processing system to determine e.g. the vehicle’s working status or other features of interest by means of simple distinction of cases based on hard coded conditions. Due to the fact that there is no way of adjusting this mechanism during runtime the sensor data and context information that the implement would be capable of providing is simply ignored. The same applies to situations where one machine interacts in close collaboration with another one. Even though exchange of data would yield tremendous potential it cannot be accomplished due to the rigid data handling approaches employed. The underlying problem that can be identified can thus be summarized as the lack of a uniform way of handling and aggregating data in multicolor machine combinations and fleets.

A typical manifestation of this shortcoming is the combination of a tractor with a seeding implement. A typical description of the working state of the tractor alone would be a ground speed greater than zero and an active PTO or three-point hitch down. For the tractor alone this might be sufficient. If one considers the implement on the other hand this is no longer true since the implement changed the intended task definition tremendously. Thus, the definition for status “working” should rather be redefined to positive vehicle speed and seed outlet open since this would result in more appropriate data that can later on be analyzed in order to optimize the farm operation.
A Modular Sensor Fusion Architecture

To overcome the shortcomings discussed in the previous sections a new approach is to be found. In order to make it applicable in agricultural scenarios there are several challenges imposed by the domain that should be considered in the design process. Another central aspect is the current exchange of system components and entire subsystems. This imposes the question of an efficient knowledge management system that is needed to integrate both hardware (i.e. sensor) and process (i.e. domain) knowledge. Due to the described situation of a very diverse selection of components, the only reasonable way to do this is to treat the system (and the information it is contributing) as one entity with a shared lifetime. This means that the knowledge enters the system as the component is connected and is removed from it as soon as the host device is removed.

An essential question is this context is the amount of hardware and process information that the system requires for each component. This question is a very central design decision at this point because one has to consider the trade-off between more sophisticated knowledge but the inability to include all physically present components (due to unavailability of this information) and very little device and process description which allows to include almost all elements due to the lower burden. We have seen the consequences of the former to an extreme extent in the previous section. Thus, this option is eliminated. Since the only viable way to overcome the shortcomings observed is to go the latter way, a minimum set has to be defined.

The consequence of this decision is that the available selection of potential algorithms for data fusion and aggregation is severely reduced. Proven and well-established methods for low level fusion like e.g. Kalman [Welch06] or particle filters [Xiong06] cannot be applied without a deep understanding of the process and the components involved. In this case approaches that rely on heuristics rather than models and therefore require far less information are the only logical choice. Even though there exists a comprehensive selection like e.g. weighted average, median- and threshold voters [Hoseinnezhad06, Parhami94] none of them has proven to be ideal candidates for application in rough and rapidly changing environments like agricultural scenarios. This is due to their inability to properly adjust to dynamic changes in the general sensor data quality due to noise inflicting conditions like e.g. severe wheel slip in a wet field vs. driving on the road. Other aspects are poor characteristics w.r.t. robustness (i.e. dealing with sensor drift and failure) and output accuracy requirements (relative to the ground truth).

A similar situation can be observed when looking for proper algorithms for data aggregation on a higher level. The limiting factor here, however, is in most cases neither the limited knowledge nor the lack of robustness but rather the restriction in available computational resources and the demands for results in real-time. Typical candidates for this class are clustering (e.g. c-or k-means), learning based approaches (like e.g. neural networks), and rule based classification [Kanungo02, Tschichold95, Ishibuchi98].

Before getting into further detail, let us first take a look at the architecture in general. An overview of the approach can be found in figure 2.
As can be seen the data handling structure is embedded into the network that is formed by a tractor and a generic implement (top of illustration). Both systems are equipped with sensor hard-wired to electronic control units (ECU), smart sensors (S) with dedicated bus interfaces, and gateways (G) that connect the tiered data bus structure. Since the selected approach enforces a component oriented rather than a machine centric paradigm the physical machine borders dissolve from the system’s point of view. This means that the physical origin of the provided contribution by a component is processed in disregard of its physical location and assignment to a machine.

The data handling system itself is structured into three separate layers with distinct functionality. The first level is called the signal alignment level. Here all data transmitted throughout the machine on the bus system is transferred into a common representation format. The required knowledge about how to properly convert those signals is provided to the system by each component via a lean XML interface. The separate files contain information like e.g. the measured physical property (e.g. hydraulic oil pressure), scaling and unit conversion factors (needed to convert the source specific encoding into a aligned representation), and a system-wide unique ID. The latter is important to assign the correct mapping to incoming data. In order to keep the overhead low, one can simply utilize the bus addresses as long as they are unambiguous. The result of this process is then centrally maintained in form of a mapping table. In order to keep the data and management overhead low this is done only once when a new device is connected.

Once the sensor data is converted one can proceed with signal level fusion. In order to be able to deliver good results, rejection mechanisms for erroneous measurements have to be established prior to the intended fusion itself. Since one cannot rely on detailed models due to the unavailability of knowledge about certain hardware aspects, other solutions have to be found. The approach taken here is to utilize aspects of the domain knowledge to remove obviously false pieces of evidence while relying on the fusion algorithms’ heuristics to eliminate the generally plausible but conflicting bits of information. Let us study this process in the following example: Consider four different entities $v_1,..,v_4$ providing groundspeed measurements to the system. Let us assume that
their values are 13.26, 14.87, 96.7, 6.05 (all in km/h). Making use of the available domain knowledge implies that the third measurement is outside of the specified plausible speed range of 0 to 65 km/h for the given machine. Thus, it is eliminated and only the three remaining measurements are passed to the fusion algorithm. It is obvious that this three-element vector still contains conflicting data, but since it is within the plausible range it is up to the fusion approach to determine the true speed based on the remaining measurements.

Once the incoming data has passed the initial check the remaining signals are grouped based on the physical property that they represent. This information is once more extracted from the sensor knowledge. Since the number of sensors per property can vary between cycles (due to the initial check and differing sensor updates rates) this process has to be performed continuously. After the signals are grouped, one faces the challenge of combining the data into a single value per physical property. This is done with the fusion algorithm. As outlined in the introduction of this section the commonly utilized signal level fusion approaches were unable to cope with the demanding conditions considered for the application scenario. This is because they have to combine a low computational demand, inherent robustness to noisy and faulty inputs, ability to function with very limited system knowledge, and optimal fusion performance at the same time. Thus, a method specifically designed for this task was developed (see [Blank10] for further details). A short overview is provided in figure 3.

![Figure 3: Schematic overview of the employed fuzzy voting approach](image)

As illustrated the algorithm employs the relative Euclidean distance of all pair permutations of the incoming data. After a normalization step they are mapped onto fuzzy sets that represent the degree of sensor agreement based on their distance. This results in a set of membership vectors of which each can be attributed to exactly two sensors that provided the data for it. Hence, each one receives a score that is then summed up for all vectors. The higher its agreement with the others, the larger the computed score is going to be.

Graphically speaking one tries to form a cluster containing a majority of the inputs in a way that the center coincides with the underlying true value that one tries to find. In order to compute the most likely correct values (based on the input) the scores are employed as weighting factors for the respective measurement value in a weighted average-like process. Furthermore the scores can be employed as a relative quality metric. Based on this information one is able to compute an overall confidence for the fusion result as well as individual ones for each sensor. In order to achieve a sufficient level of accuracy with this method, a threshold has to be employed to remove all
measurements that represent outliers caused by excessive noise or sensor failure. The graphic interpretation for this is a circle around the center of the formed input cluster that is employed as a barrier. This means that all results that reside outside of the circle will not influence the result and the sensor will receive a confidence rating of 0. Since this threshold has to adapt to the available overall sensing quality, a feedback loop-like mechanism is introduced. Its intention is to keep the output confidence level in a range between 0.1 and 0.9 on a 0 to 1 scale (with 1 being the best).

Since this approach requires a minimum of three inputs, an adaptive weighted average approach is included for properties with only two available measurements at one point in time. Due to the limited space available, it will not be presented in detail in this paper. However, the basic idea is quite familiar to the one of the fuzzy voter above. Once more a heuristic based on the distance in sensor readings is employed. This time, however, the signal history is considered in order to detect suspicious changes in the signal of a sensor.

Moving up to the last level of the hierarchical structure one reaches the high level fusion. The general purpose of this level is to aggregate the fused measurements and process them in order to extract specific patterns or features. Therefore it is frequently addressed as feature level fusion. In our application, the task pursued on this layer is vehicle status determination. As said before, there exists a rich selection of approaches that can solve this problem without problems. However, their common shortcomings are the lack of real-time capabilities and a severe demand for processing power that cannot be satisfied by ECUs and terminals typically found on an Ag vehicle. Thus, the design task was to explore the possibility of simplifying the data sets in order to lower the computational demand and ensure results in proper response time.

To master this challenge, two techniques could be identified that mutually complement each other in a way that ensures best possible results and scalability. The approach pursued here is to initially use a rather simple fuzzy classification approach. For this purpose the domain knowledge is formulated as fuzzy rules on this level. This means that typical value profiles are assigned to the relevant properties in order to specify vehicle state. In an exemplified scenario for a forage harvester and the state “harvesting” this could be e.g. a specific speed profile, a typical metric for mass flow through the system and the position of the header. Based on this classifier one can compute a rating for each fused input and combine them to form an evaluation metric for the potential state of the vehicle. In the suggested system one can even go one step further and additionally employ the confidence value derived in the signal level fusion for each measured parameter. Thus, one can base the decision towards the most likely current state not solely on the numeric fusion result and the classifier but also on the vagueness of the inputs. In technical terms this means that instead of a single value, a parameter range is evaluated with the fuzzy sets. Thus one receives a two dimensional field instead of a single number to quantify the state probability upon. If this process is performed for all state definitions of interest, one will be able to employ a simple maximum norm in order to derive the most likely state.

The downside of such a simple fuzzy approach is that only a single point in time is considered per cycle while the system history is neglected. In order to enhance the functionality of the state classification one can append another process on top that offers more capabilities. In our case this is a hidden Markov model (HMM) that enables the user to model processes as a sequence over time. The main focus in our application is that such an approach allows to include more thorough domain knowledge as it becomes available. An example for such advanced process information could be e.g. typical state transition probabilities that can be derived from previous machine utilization data. By inputting the results of the previous fuzzy classification step into the HMM the

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1 For a detailed description of HMMs and their application the interested reader can be referred to [Bilmes06]
computation demand (that is typically quite high) can be significantly lowered since the algorithm solely has to deal with state candidates instead of having to bother with a load of fused sensor measurements. This is especially important when considering the complexity of the model and the resulting computational load.

The beauty of a combined approach like this is that it offers an easy to use solution sufficient for all basic needs of the user while providing advanced solutions for experienced operators. At the same time one is able to maintain modest computation demands. The resulting system therefore scales very well with the machine complexity and skill level of the user.

Conclusion

In this paper a modular approach to sensor fusion for agricultural machines was introduced. Due to the consequent enforcement of generic design this approach offers efficient data exchange and processing between heterogeneous machine/implement and machine/machine combinations. This data-centric methodology encourages global exchange of data across physical borders. Therefore, it helps to overcome the shortcomings like e.g. inconsistencies and static, single-machine-centric data processing that we experience today. In order to keep the information management overhead low, a lean mechanism based on component supplied meta-information is proposed. This fact relieves the operator from manual configuration that is tedious, time consuming, and error prone. Furthermore, its modular characteristics make it easy to use and adapt/extend to the specific needs that might exist. Moreover, it allows the user to formulate process knowledge in a very intuitive way.

The overall lean design that matches the restrictions of embedded systems (i.e. real-time constraints, quite limited computational resources and memory). Furthermore most aspects can be realized even on today’s platforms with their limited data bus bandwidth resulting in comparably low data update rates.

A more manufacturer focused aspect of the system is that it eases the development of new sensor data-based components and subsystems since it offers an abstraction layer for the sensing hardware. Therefore, the designer does not have to worry about the specific origin of a piece of information anymore but can rely on a pool of aligned and reliable measured parameters.

Outlook & Future Work

A major aspect of the work presented in this paper is focused on the management of distributed hardware and process knowledge provided by heterogeneous sources. The same idea is pursued in the iGreen project. The scopes of both undertakings mutually supplement each other in an ideal way. iGreen focuses on the exchange of location-based information via a data cloud spanned by components distributed over the internet. The work presented in this paper, however, targets the information exchange and processing among various pieces of agricultural machines that cooperate to achieve a common task. Since the potential benefit from global data exchange is highly dependent on the quality of local machine data it is straight forward to combine both approaches by providing a data exchange interface. More than that, one will enable component and domain knowledge exchange on a global scale among different stakeholders by utilizing the provided infrastructure. This way one will be able to tap into the data cloud for the benefit of all participants in the future. Applications like e.g. integrated fleet management and monitoring could be potential results of this new dimension in data management.
Apart from this, another interesting field of application could be the ISO 11783 standard. Since this standard emphasizes the need for interaction between different machines in the agricultural world, it makes sense to take the next step towards a closer coupling of components beyond what is already common practice today.

As for the system itself, the next objectives outside of the simulated test environment are planned for the near future. In order to demonstrate the practical benefit that this approach has to offer, the migration of the software towards a real-time environment on an actual demonstrator vehicle is currently performed. The goal is to provide data gathered during field tests that underline the practical applicability and benefits of the presented methodology.

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