Use of automated systems for recording of direct and indirect data with special emphasis on the use of MIR milk spectra (OptiMIR project)

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Abstract

A current tendency in developing tools to support farm management is to make use of advanced sensors closely associated to animals, facilitating the collection of large quantities of data ideally at a low cost without perturbing the animal itself. On a dairy farm level, sensors measuring milk conductivity or pedometers measuring mobility are often cited as examples. This introduces the concept of "precision livestock farming" where a given "bioresponse" captured by a "biosensor" allows the creation of feedback to adjust the "bioprocess". Such on-farm systems are often restricted to a given farm and they are mostly strictly separated from standard performance recording systems. In dairy cows, a particular rich source of information to detect a "bioresponse" is milk and its (fine) composition. Standard milk analysis undertaken in milk recording schemes by mid infrared spectroscopy (MIR) generates spectral data that reflects the milk characteristics. Therefore, spectral data directly reflects the metabolic (e.g., energy balance) and health (e.g., udder health) status of the cow. The use of MIR spectral data to predict fine milk components (e.g., fatty acids) is now becoming commonplace. However the use of MIR spectral data could provide an even more direct method to assess the "bioresponse" in relation to health, fertility, feeding, milk quality and even rejection of pollutants. For this reason, 12 EU milk recording organizations and milk laboratories together with 6 EU research groups have joined forces to develop the North-West Europe INTERREG IVB Project OptiMIR (*www.optimir.eu*). As a first step to use spectral data for developing decision support tools, the project includes the development of methods to standardize spectral data generated by various apparatuses in different laboratories. Through the OptiMIR project, health indicator traits from milk analysis either through the prediction of milk components (i.e. lactoferrin) or through the direct assessment of the health status of the cow (i.e. clinical mastitis) will become available. These data can then be generated in routine milk recording and can be stored in a central database. Because generating MIR data at the on-farm level is still difficult and expensive, the use of near infrared (NIR) spectroscopy is currently also under investigation by other groups. For a comprehensive use of fine milk composition, as for other automated sensors, the optimum would be a close and bi-directional interaction between in-line on-farm systems and central databases in order to contribute to the successful implementation of powerful health monitoring systems and decision support tools.

Keywords: milk composition, milk spectra, indirect health data.

Introduction

The use of direct milk yield meters and similar sensors in robotic milking units within fully computerized milking parlours linked to farm computers and herd management systems, is often seen as a classical case of "precision livestock farming" in dairy cattle. A current tendency in developing tools to support farm management is to make use of advanced sensors, often closely associated to animals, facilitating the collection of large quantities of data. On dairy farms, sensors measuring milk conductivity or pedometers measuring mobility are often cited as examples. A very comprehensive review was recently published by Rutten *et al*. (2013). The concept of "precision livestock farming" can then be summarized where a given "bioresponse" is captured by a "biosensor", which allows the creation of feedback by using the collected data in an appropriate model to adjust the "bioprocess". (e.g., Aerts *et al*., 2003). Figure 1 shows a typical set up.

Based on their review Rutten *et al*. (2013) distinguished four levels of use of sensor data: I) technical, II) data interpretation, III) integration of external information and IV) decision making. They identified that in dairy cattle the available systems are generally poor when considering levels III) and IV).

In contrast to many other species and production systems, dairy farming has also another, well-developed historic dairy herd management approach which relies on classical performance recording, mostly supervised by technicians, on centralized milk testing and on centralized databases (ICAR, 2012). These data are also the primary source of dairy cattle data used in animal breeding (Interbull, 2012). Recent research has extracted additional information from these performance data (e.g. Mayeres *et al*.,2004) and to improve advisory tools based on standard performance recording data.

Currently the uses of on-farm computers based systems and centralized performance-recording based tools are considered as two opposite "worlds" for dairy cattle management. However, in practice, the use of automated systems for

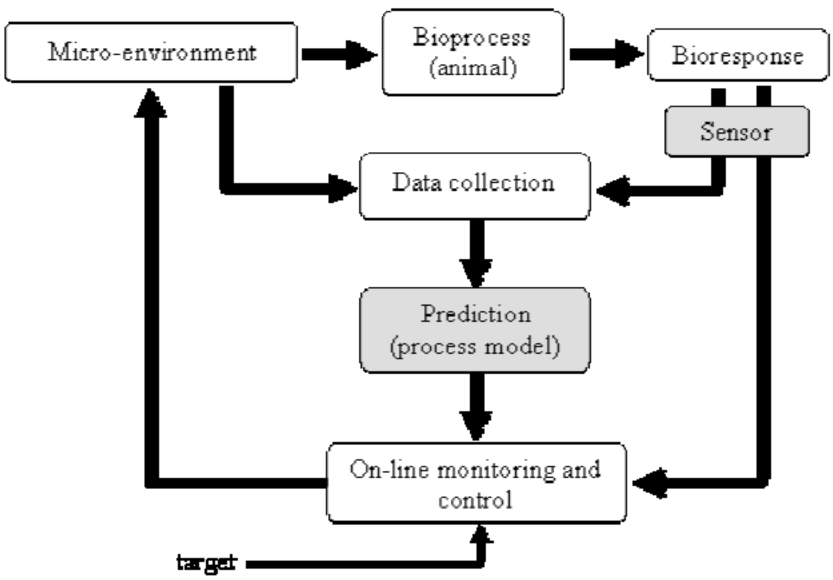

Figure 1. Typical set up of model-based process control (from Aerts et al., 2003).

recording of direct and indirect data is becoming very important, especially for novel traits. An additional source of information could be available by maximizing the potential of already existing off-farm analysis tools. Only through the availability of these novel traits research and development are possible leading to their application in management and breeding. The present paper focuses on the use of milk composition and especially the use of mid infrared (MIR) milk spectra as a rich source of new information. Particular emphasis will be given to the new OptiMIR project (e.g. Massart, 2011) its rationale for the innovative collection of health data, the use of this data for research, and the dissemination of the results of this research to the farmers.

Milk composition and animal health

It is well known that milk composition, and in particular, milk fat, protein content and fatty acid profiles may be significantly altered due to a variety of factors, one being metabolic or health status of the animal. Therefore changes in milk composition are considered potential indicators for the status of a given animal (e.g., Hamann & Krömker, 1997). Milk becomes a potentially particular rich source of information if the "bioresponse" in milk can be captured through its (fine) composition. Standard milk analysis undertaken through milk recording schemes by mid infrared spectroscopy (MIR) generates spectral data that reflects the overall milk composition. The prediction of animal health from milk MIR spectra can be through two approaches:

1. first predict specific milk components (indicator traits) from milk MIR and then, using regression models including these milk composition traits, predict animal health, or
2. predict animal health directly from the milk MIR (Figure 2). Alternatively indicator traits as defined in approach (1) are currently studied as alternative and additional sources of information for health traits as fatty acids in milk for fertility

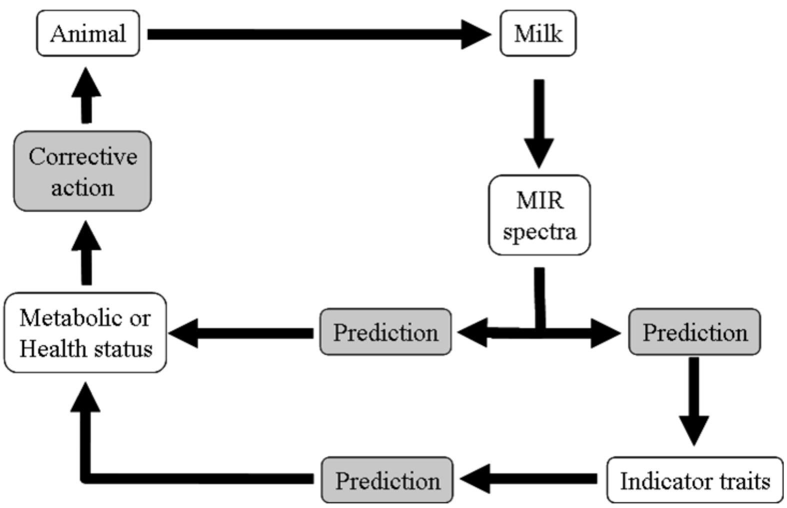

Figure 2. Pathway for direct and indirect prediction of metabolic or health status traits.

(e.g. Bastin *et al.*, 2011). The use of somatic cell count in conjunction with mastitis is another well-known example even id somatic cell count is a component not predicted from MIR spectra.

Predicting health relevant milk components from MIR spectra

A powerful tool to detect milk composition is the use of MIR spectra to determine fat, protein, urea and other major components. Soyeurt *et al.* (2006) also proved that minor milk components can also be predicted from MIR spectra as long as a calibration data set can be created with reference values that reflect the underlying variability and the variation in the component under investigation is reflected in variability in the associated spectrum.

A well-known example of the indirect use of milk composition is the detection of ketosis. Research showed the feasibility of predicting of β-hydroxybutyrate (BHB) and acetone in milk from MIR (de Roos *et al.*,2007). However de Roos *et al.* (2007) also reported, which was later confirmed by van der Drift *et al.* (2012), that indirect detection of subclinical ketosis with BHB and acetone was associated with large prediction errors. A contributing factor to reduced accuracy of prediction of animal health from MIR predicted indicator traits, is the accumulation of prediction errors as shown in Figure 2. In this context the prediction errors reported by de Roos *et al.* (2007) remained rather large and as shown in their results the relationships between predictions and reference values were not clearly linear.

Similarly novel indicator traits for animal robustness or udder health were recently made available [i.e., lactoferrin, (e.g., Soyeurt *et al.* 2007)]. Again even, when predictions of the traits can be made reasonably precise the accurate relationship between these derived traits and animal health is more difficult. Based on these two finding (avoiding cumulating estimation errors), the new direct approach, featured inside the OptiMIR project, was developed.

The OptiMIR project

The basic novel scientific idea underpinning the OptiMIR project is that direct use of MIR spectral data could provide more informative "bioresponse" to relate to health, fertility, feeding, milk quality and even rejection of pollutants. For this reason, 12 EU milk recording organizations (MRO) and milk laboratories together with 6 EU research groups have joined forces to develop the North-West Europe INTERREG IVB Project OptiMIR (*www.optimir.eu*) as equal partners around the topic of direct use of MIR spectra for management use. The first novel component of OptiMIR is therefore that this project was built around a clear path from the acquisition of data towards to the dissemination of results, this last point becoming a major priority in many European research framework projects. A second novelty of this project is the concept of management information traits (MIT). A good example is that instead of trying to use an indirect trait as lactoferrin with an a priori cut-off level, a directly useful MIT as "probability of having a subclinical mastitis" was defined. As these MIT are directly describing status, they can be easier used in a decision making tool.

In order to use directly MIR spectra, in a first step the OptiMIR project includes the development and use of methods to standardize spectral data generated by various apparatuses (Grelet *et al.*, 2012) across spectrometers used in the project. The third originality of the project is the creation of a transnational research data base that allows collating relevant data from different partners in order to increase its relevance for research and development. Respecting the original data ownerships, this data base will also continue to exist and the stored data, at least partially, potentially contribute to further projects which can in exchange use the OptiMIR partnership as dissemination channel. Finally, by developing expertise and some joint tools, OptiMIR will help create and disseminate the acquisition of health indicator traits from MIR milk analysis either through the prediction of milk components or through the direct assessment of the health status of the cows. These data can then be generated in routine through milk recording and can be stored in their central databases.

Current status of interaction between on-farm and off-farm systems

Very early with the first sensors (classical milk yield meters) becoming available performance recording agencies have started to develop ways to recover this on-farm data. Basically two strategies were pursued. The first strategy is the development of own on-farm management systems, the PCDART program (Dairy Records Management Systems, Raleigh, NC, USA) being an example. Unfortunately this limits the choice for herd owners and is considered not necessarily optimal by them because of their preference for another system. A second strategy was to develop methods to export the data from the farms to central databases independently from the manufacturers of the different on-farm systems. Again the natural limit that appeared was the need or, unfortunately, the lack of common exchange standards. Therefore in many countries different customized tools are under development or already deployed to get access to this data. In the Walloon Region of Belgium the Walloon Breeding Association (AWE) is currently implementing Ori-Automate, a tool developed in collaboration between France Conseil Elevage (FCEL) and Valacta (Dairy Production Center of Expertise Quebec-Atlantic, Canada) based on Valacta's Trans-D software. Ori-Automate is a bi-directional interface tool that links farm management software to performance-recording databases, being multi-manufacturer and able to be pluged-in directly into on-farm data bases (Saunier *et al.*, 2012).

There are two other hidden advantages in a bi-direction approach for health data acquisition. First on-farm sensor-based tools need to access basic animal data in order to operate. By linking up with the recording agencies farmers no longer need to enter this information, potentially even several times, as it is readily available in the central databases. This obviously limits potential errors especially in animal identification and improves health data quality. Also current on-farm systems when provided by different manufacturer are seldom designed to exchange data. By communicating with Ori-Automate or similar systems, the exchange between on-farm tools is, indirectly, established which will improve quantity and quality of health data.

Use of on-farm data and interaction with OptiMIR

Because generating MIR data is still difficult and expensive, alternative techniques have been proposed (Rutten *et al.*, 2013). The use of near infrared (NIR) spectroscopy is also under investigation (e.g., Nguyen *et al.*, 2011) to relate the generated spectra to milk composition. Initial results are promising; however off-farm MIR measurements are still more reliable and, as shown in the OptiMIR project, they can be harmonized and standardized among apparatuses. Stability of on-farm sensors in general over time is still uncertain and rarely reported. Experience with MIR showed that this could be an issue that has to be considered by manufacturer of sensors. For a comprehensive use of fine milk composition, as for other automated sensors that are generating relevant data, the optimum would be a close and bi-directional interaction between in-line on-farm systems and central databases. These databases should contain also data obtained by off-farm methods (e.g. MIR spectra) that allow to benchmark and correct on-farm systems. Optimal would be the use of both data sources for health monitoring system. By their open conception the tools developed in OptiMIR can take advantage of additional on-farm measurements as soon as they become available. It can also provide useful feedback as soon as a bi-directional exchange

Conclusions

Currently, many automated sensors are used on-farm to record health related data. Interaction between these automatic sensors, off-farm systems and centralized databases is still weak and highly depending on powerful data exchange protocols and tools. Off-farm systems based on MIR spectral data are currently being developed inside the OptiMIR project. This project has a certain number of specific features including the close association between MRO and scientific partners, the building of a transnational data base and the joint development of advisory tools. By their open conception tools developed in OptiMIR can take advantage of on farm measurements, but can also provide useful data back to farms as soon as bi-directional data exchange can be organized. Finally the use of automated systems for recording of direct and indirect data on-farm and off-farm will be a major source of health relevant data in the future.

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