The use of a light scattering-based sensor in Precision Dairy Farming (PDF)

R. Saltman[1], S. Deshpande[2,*] and B. Sudarsan[3]
[1]*RLS Management Solutions LLC, Cazenovia, NY, USA*
[2]*SpectraDigital Corporation, Guelph, Ontario, Canada*
[3]*SomaDetect Inc., Halifax, Nova Scotia, Canada*
[*]Corresponding Author: Roger Saltman, rls30@cornell.edu

Abstract

Monitoring health and production-related parameters of the individual cow in a real-time, cost-effective manner can reduce the costs of production and veterinary care. We will report on a Light Scattering Sensor (LSS) from SomaDetect Inc. The LSS is a self-contained in-line device consisting of a milk channel between a laser and a scattering detector that is attached to the milking line in a dairy parlor or on a milking robot. It requires no operational actions from farm personnel or any consumable reagents. During milking, the LSS collects and transmits a series of images to the cloud. The images are analyzed using proprietary machine learning and artificial intelligence algorithms that currently measure somatic cell count and determine pregnancy status at 18 Days Since Last Heat (DSLH). Other milk and cow attributes are currently being researched. This data, transmitted to the farm in near real-time, can be used to determine udder health and reproductive status of individual cows and groups of cows.

Keywords: light scattering, image analysis, somatic cell count, in-line testing

Introduction

The economic challenges of dairy production over the last 30 years have led to increased herd consolidation as well as a shift to larger herd sizes. The inherent economies of scale allow producers to be more efficient by spreading their fixed costs over more cows (MacDonald et al., 2020). However, increasing herd size has challenged dairy managers in their ability to monitor individual cow health and detect sickness or other animal production attributes in a timely manner (Barkema et al., 2015). The concept of monitoring individual animals, whether the entire herd or a subset, for selected health-related parameters is not new. Various technologies for monitoring the herd, groups of animals and even individual animals themselves continue to be more prevalent on these larger dairy farms. Examples include measuring animal movement (total time walking in the barn), resting time, time eating at the bunk, animal rumination rate, body temperature, walking behavior, thermal imaging, and other parameters have all been developed to help the manager monitor the dairy. Technologies which can work in the background to acquire health-related data without requiring operational action or changes in daily routines by the dairy's personnel are highly desirable. This paper provides a high-level description of a light scattering-based sensor in a dairy farm production setting and the initial results of a study aimed at predicting if an inseminated cow is pregnant or not at 18 days post-breeding.

What is light scattering?

When light, i.e., electromagnetic radiation, interacts with matter, it can be absorbed or scattered (Hahn, 2009 and references therein). During absorption, light interacts with particles chemically, transferring the energy to the particles as a result. The scattering of light occurs when the incident light interacts with the electrons of particles, causing them to oscillate at the same frequency as the incident light and giving off light of the same frequency. It is the oscillations that produce light termed "scattered light." The scattered light provides both structural and chemical information about the particles (Berne and Pecora, 2000). The scattering is dependent on the particle size and shape, the concentration of the particles in the media, and, the refractive index of the particles relative to the media in which they are suspended. The refractive index is representative of the chemical composition of the particle and this chemical composition difference is what results in scattering having a specific pattern associated with the refractive index.

In the case of milk, which consists of many different particles of varying shape, size, chemical composition, and number of particles per unit volume, the nature of the scattering is what is termed “multiple-particle scattering.” That is, the scattered light has resulted from interactions with the many particles present in the milk. The mathematical expression for deriving or predicting multiple-particle scattering events has not been developed and calibration models are the best way to approximate this phenomenon. It is for this reason that machine learning techniques are useful for assessing milk characteristics.

Materials and methods

The light scattering instrumentation (the sensor) consists of a laser to provide the incident light which is directed to a light sensor (camera) through a flow channel that directs the raw milk between the laser and the camera, and an embedded computer that controls the image acquisition sequence by the image sensor and uploads the images to the cloud. The sensor can be attached to the milking line using standard hoses used in milking parlors. No chemicals are added to the milk which is an important consideration with respect to consumer safety. Figure 1 below is a diagram of the optics and electronics of the SomaDetect sensor.

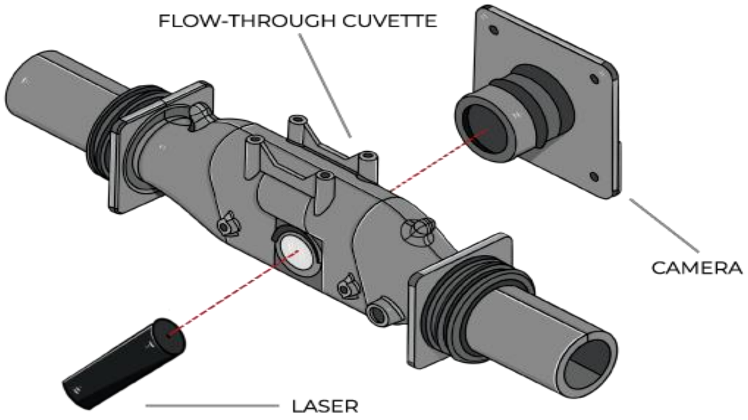

Figure 1: A diagram of the optoelectronic components and the optical arrangement to obtain a light scattering signal.

The laser emits light of 780 nm wavelength which enters the flow-through cuvette containing the milk from the cow in the milking stall or on a robot. The scattering of the laser light is detected by the image sensor and uploaded to a server. The image sensor records a scattering pattern that consists of circular intensity rings that represent scattering intensities at various angles with respect to the laser beam. The image sensor can be controlled through software to collect images of the milk flow at any preset intervals. In addition, the sensor resolution can be adjusted to optimize the number of pixels that are collected. The greater the image resolution, i.e., higher number of pixels, the more accurate a determination of the scattering intensities can be made. Typically, one image is taken per second during milking and the images are sent to the cloud for analysis and reporting. However, the analysis step consists of using various arithmetic operations on multiple images to derive some characteristic of the milk composition or substances in the milk.

With the exception of the data in Figure 4, the data cited in this discussion came from cows being milked in a parlor with the SomaDetect in-line sensor installed and with no additional treatment. The images shown in Figure 2 are what is produced on a typical farm with these sensors. The plots in Figures 3 and 4 were obtained from the images in Figure 2 using established image analysis techniques whereby an intensity plot can be drawn by selecting an image of interest and averaging the pixel values along the y-axis (pixel intensity) to the corresponding x-axis (the scattering angle as measured from the center of the laser). The data in Figure 3, was derived from the sensor images of milk taken from a cow known to be treated with antibiotics. The observed light scattering changes resulting from the presence of antibiotics confirmed that the milk needed to be diverted from the bulk tank. For the data shown in Figure 4, milk was spiked with a known quantity of progesterone and tested in a sensor as described but not connected to a milk line in the parlor. This was done in a laboratory setting as it was desirable to obtain the light scattering signals as soon as possible after the addition of progesterone in case of degradation of the progesterone and to avoid the contamination of the milking equipment on a farm by a substance not in use at a dairy farm.

Results and discussion

Because milk is composed of particles of various size with differing chemical makeup and volume proportions, the interpretation of the pattern is challenging. However, it is possible to take an empirical approach to calibrate the sensor. The most straightforward approach is to use milk of known characteristics such as somatic cell counts (SCC), fat content, or others such as antibiotics and progesterone to obtain light scattering patterns that can be stored and used to develop a quantitative model against which milk of unknown characteristics can be compared. This was described in the two patents (Deshpande and Moyer, 2016 and Deshpande et al., 2020) that have been filed. While the models for SCC and fat can be approximated using imaging software, machine learning and artificial intelligence-based methods are useful for detecting the presence of dissolved substances such as antibiotics and progesterone owing to the scattering at several different angles.

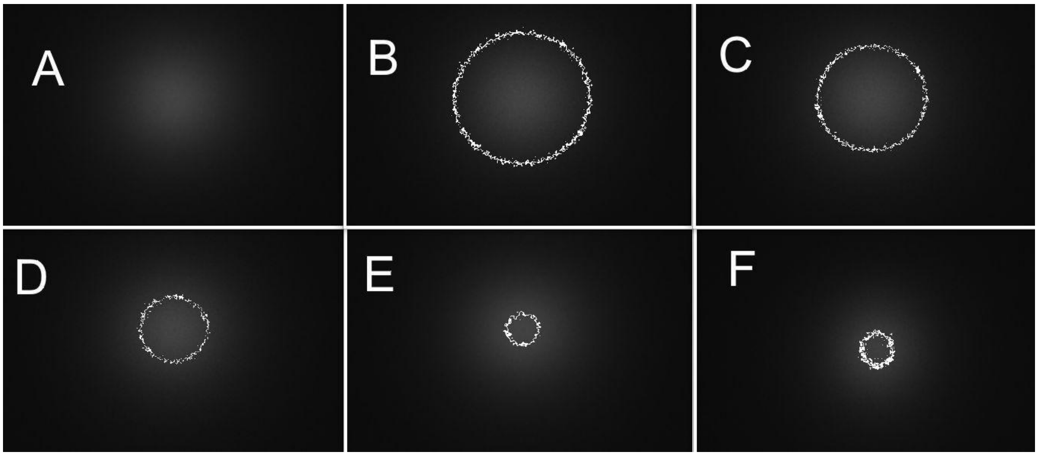

Figure 2: Panel A is a scattering image acquired from milk with 3.9% fat and a SCC of 325k. Panels B to E highlight the scattering observed by using software to display pixels of a given intensity in Panel A. Panel F shows a scatter pattern from milk with 3.9% fat and SCC of about 2900k and has a quantitatively greater number of pixels at the scattering angle dominated by scattering from SCC. Note that the lighter color of the rings is highlighted for visual purposes and the center of the image in Panels E and F is different as the data was obtained from two different sensors.

The complexity of a light scattering event can be seen in an image acquired as shown in Panel A in Figure 2. This image is from milk that has a fat content of 3.9% and a SCC of 325k. A visual inspection shows no obvious features discernable to the eye. However, a closer analysis of the image by highlighting the pixels of similar intensity using an off-the-shelf image analysis software (such as ImageJ from the National Institutes of Health available at https://imagej.net/ij/index.html) clearly shows the scattering pattern as a series of rings highlighted in Panels B to E. It should be noted that the image analysis software was used only to highlight the regions of the image of a given intensity to demonstrate the scattering pattern. Although there are many more rings, only a few were selected in the Panels below to demonstrate the scattering pattern. Each set of rings are indicative of a structural and chemical component of the milk. Typically, a light scattering signal is displayed as a cross-section profile of the angular intensity but herein provided as an illustration of the origin of a scattering profile.

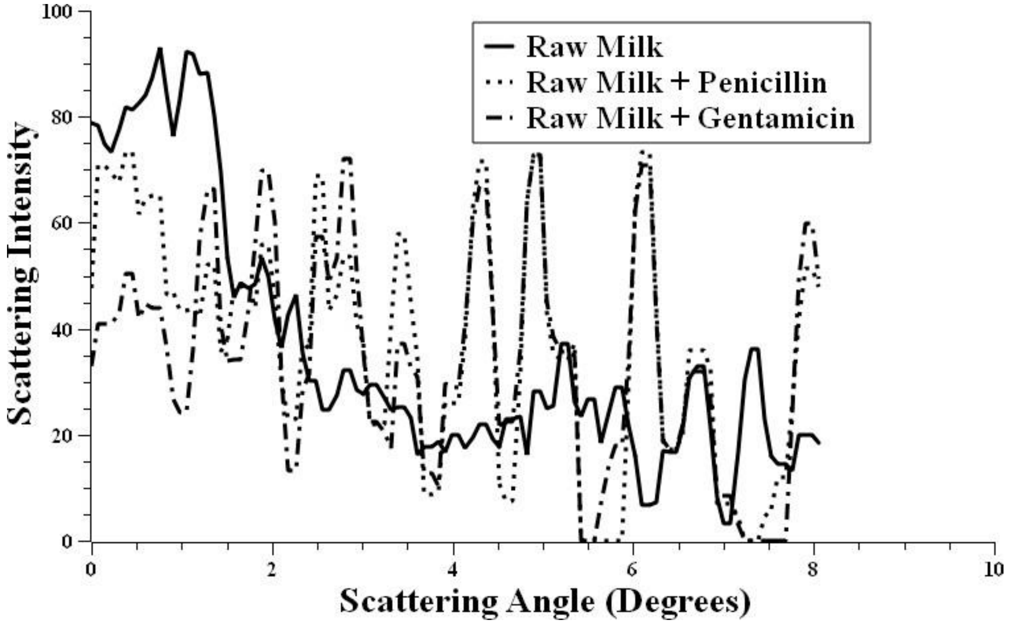

Figure 3: Plot of the scattering intensity versus the scattering angle for raw milk (solid line), and raw milk with penicillin (dotted line) and gentamicin (dash-dot line). The scattering intensities were obtained from the standard deviation of 50 images which allowed for the detection of low intensity peaks.

The development of a quantitative model consists of assessing the regions of the image where there are changes in the light scattering pattern due to some change in a milk characteristic. A simple illustration of changes in light scattering intensity due to a change in some measured characteristic of milk can be seen by comparing Panel E with Panel F. In Panel F, the scattering pattern from milk having about 3.9% fat and a SCC of 2,900k shows that an increase in SCC results in an increase in the density of the pixels when compared with pixels at the same scattering angle shown in Panel E (which was acquired from milk with a much lower SCC); this was the most prominent change in comparison to other angles with respect to the increased somatic cell count and interpreted as representing the scattering from the somatic cells.

In the case of other substances such as antibiotics or progesterone, the light scattering data is more complicated as there are changes in the scattering intensities at several scattering angles. Furthermore, because these substances are dissolved in the milk as opposed to being present as particles, a pixel-by-pixel standard deviation is calculated on a series of images to assess for the small intensity scattering profiles associated with these substances. Figure 3 shows a plot of the cross-section of a series of scattering profiles obtained from raw milk as well as raw milk containing the antibiotics penicillin and gentamicin (as determined by a laboratory test). As the plots shows, the detection of peaks can be challenging and machine learning methods are almost essential to discern the peaks.

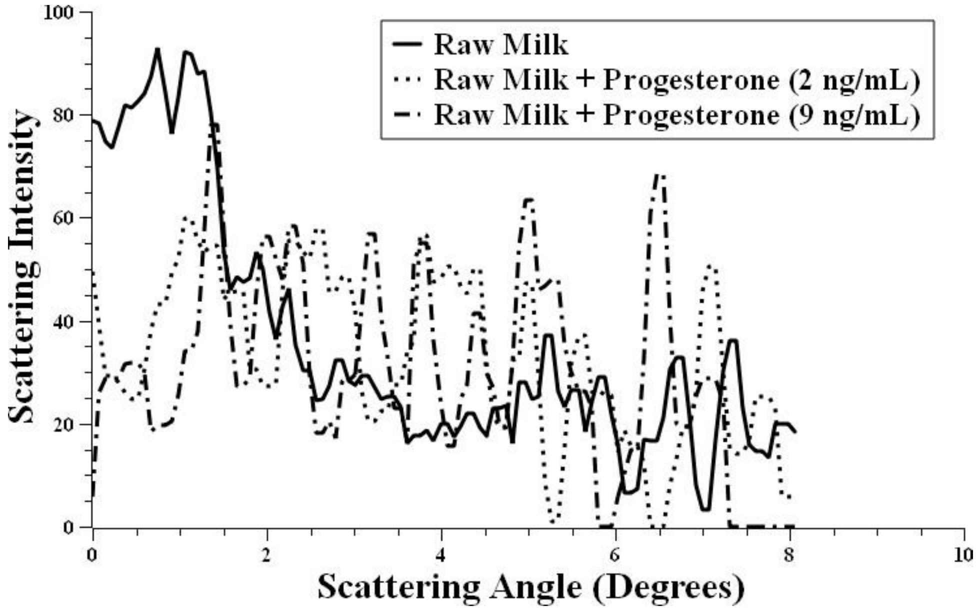

Figure 4: A plot of scattering intensity versus the scattering angle for raw milk (solid line), raw milk with 2 nanograms/mL progesterone (dotted line) and 9 ng/L progesterone (dot-dash) using similar experimental approach of using about 50 images as previously described.

Similarly, Figure 4 shows the plots of the scattering profiles obtained in the same manner from milk that was prepared with known quantities of progesterone. Changes in progesterone levels are associated with various phases of the estrous cycle and changes in light scattering can thus be associated with the estrous phase in the cow. Once again, as this substance is essentially dissolved in the milk, a standard deviation was calculated after the acquisition of 50 images. The complexities of the scattering peaks are better analyzed through machine learning models. However, before light scattering data can be used for a particular determination, measurements should be carried out to assess if there is causality between the physical characteristic being determined and the light scattering signal. For this reason, signals such as those in Figures 3 and 4 are important because they demonstrate that the light scattering changes associated with some milk characteristics of interest to the dairy producer, e.g., the presence of antibiotics or the level of progesterone, can be observed; however, modern analytical methods such as machine learning for interpreting light scattering signals are essential for analysis.

As the model was being developed, it became apparent that using the existing practice of ultrasound for determining pregnancy could be just as predictive as hormone assays. A supervised machine-learning model was developed to determine the pregnancy status of inseminated cows in our trial. The scattering signals obtained from each cow for every milking were stored for analysis. On the 18th day after insemination, a risk assessment model was run to estimate the risk index of a potential pregnancy loss for every cow in the group. As the gold standard, an ultrasound check was performed at 30 days post-insemination to determine if the cow retained her pregnancy. It was noted that the model was capable of predicting if a particular cow was at risk of abortion at around the 18-day mark. Table 1 describes the results of our first two trials of a model to predict if inseminated cows were open or pregnant at 18 days after insemination. Trial 2 describes the results from the second week of the trial where the model performance was refined and there was a marked improvement.

Table 1: A summary of a machine learning model performance for predicting open cows

Study	Model Prediction	Model Performance
Trial 1: 177 Cows	131 predicted Open	74%
Trial 2: 67 Cows	60 predicted Open	90%

This 18-day pregnancy status solution had consumed more resources to develop in terms of time, data and computational power when compared to other models described in this paper. There were several challenges and strategies which needed to be adopted when it came to preparing the training data. Significant expert advice was necessary to avoid training on the effects of confounding hormones in milk that are present so early post-insemination. We have designed continuous learning systems and feedback loops to respond to model drift and ensure the best fit to accommodate changing farm conditions. Although such end-to-end machine learning systems are costly to develop, their performance is expected to be able to respond dynamically to changes in farm conditions. For full adoption of the sensor on a dairy to predict lack of pregnancy risk, the system would have to demonstrate a high level of sensitivity and accuracy. This will lead to the farm being able to identify and re-breed the open animals earlier. Realizing that each extra day open may cost a dairy farm at least US $3 per cow, the economic value gained by the dairy farm through the use of this alternative (sensor) technology to find open cows and re-breed them sooner can be significant.

Conclusions

Light scattering technologies are not without limitations. As with any empirical analytical technique, care must be taken in the interpretation of the results. In the case of the images acquired by the SomaDetect sensor during milking, each image is only representative of the milk that is in the path of the laser. It is well known that cisternal milk is not uniform and there are variations in the milk components during the milking. As a result, the data needs to be considered as part of a more complete assessment of a particular cow by the dairy manager. That is, it is possible that a given cow may have a propensity to have a wide variation in SCC without being indicative of a mastitis infection so the producer may choose to simply monitor the animal rather than initiate a treatment. Since a light scattering determination can be made at each milking, it is reasonable to expect that the results can be considered over a period of several days to see if there is a trend that needs to be addressed. This is where the precision monitoring can have an impact on the status of the individual cow and, by interpolation, on the herd. As the Precision Dairy Farming toolbox continues to evolve, better solutions for dairy management to maintain the health of the cow as well as the herd will become available. The light scattering sensor developed by SomaDetect is an example of an in-line technology that provides dairy producers with valuable udder health and reproductive data related to cow and herd health and can provide significant value to modern dairy practices.

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