Inline mastitis detection system measuring the electrical conductivity of quarter milk

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***Abstract*—Dairy profitability depends on the quantity and quality of the produced milk. Bovine mastitis is the infection of udder tissues of cows that reduces both, and therefore it causes considerable economic damage to milk producers. Nowadays, the most widely adopted method to detect mastitis is by determining the somatic cell count per milliliter of milk. However, it requires qualified personnel and sometimes the results take a long time to be available, hampering an effective solution. The electrical conductivity of the milk could also be used, but if the test is done manually by an operator neither is effective, since affects the normal operation of the parlour.**

In this work we propose a mastitis detection system based on the measuring of the electrical conductivity of the milk of each quarter during the milking. A new milking claw is designed to include the conductivity traducers inside it, which are connected to the rest of the measuring unit. As a result, the only necessary modification to the milking machine is to replace the original milking claw with the new one. The system also includes a central unit to process conductivity samples sent by each measuring unit to determine if a cow has mastitis or not. A prototype is successfully tested in field, obtaining a precision of 65% and a recall of 64% for infected cows, approaching to the state of the art. Nevertheless, our approach is, to the best of our knowledge, the first proposal that allows a cost-effective solution since it can be integrated to existing milking machines and capable of issuing early warnings.

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

The management of the health of dairy cows is critical, since it affects directly farmers profitability through the quality and quantity of the produced milk. The quality of milk is determined by the correct proportion of solid components (such as grass, protein, lactose and minerals), minimum microbial load, free of disease-causing bacteria, minimum of somatic cells and free of chemical waste. Bovine mastitis is the persistent, inflammatory reaction of the udder tissue due to physical trauma or microorganisms infections. It is one of the most important factors that affects the quality of milk and it also reduces the yield milk and the well-being of cows. As a consequence, mastitis causes important economic losses associated with the reduced milk quality and yield.

There are two types of mastitis events: clinical and subclinical. Clinical event affects the structure of milk (change colour and flakes), udder (higher temperature) and also the general condition of animals may deteriorate. On the other hand, subclinical event not presents visible changes in milk. So, most of these latter events are unobserved and untreated, which represent a huge problem because the proportion of subclinical events are bigger than the clinical events. Exists several diagnosis mastitis tools, some of them are currently used in the industry. Tests are based on that mastitis changes the milk composition, such as Somatic Cell Count (SCC), California Mastitis Test (CMT) and Electrical Conductivity (EC) measurements. SCC's method is commonly realized in specialized laboratories, while CMT requires qualified personnel, like a veterinary technician. EC measurement test relies on that the milk's ionic composition from a cow with mastitis changes, increasing its electrical conductivity. Consequently, this method is increasingly used in the dairy industry. However, EC in milk is also affected by age, type, lactation rank, milk yield, anatomical and physiological characteristics of udder stress, season, nutrition, shelter conditions, milking technique and mastitis.

Several works [1], [2] analyze and compare the of this methods, concluding that EC measurement could be an efficient mastitis detection method. Moreover, there is a stronger correlation between mastitis and quarter milk electrical conductivity than between mastitis and electrical conductivity of the milk's mix [3]. So that, measuring the EC of each milking quarter improves significantly its effectiveness.

Ferrero et al. [4] propose an low-cost electrical circuit to measure EC quarter milk, while Muñoz et al. [5] presents a electronic interface to measure EC in liquids. On the other hand, signal processing and pattern recognition techniques has been applied for improving the mastitis detection's results from EC measurements [6]–[10] and also considering other milking data [11]. Real-time measurements of the rumen temperature by utilizing an ingestible biosensor with wireless communication enable the farm manager to receive mastitis alert messages when a rise in a cow's body temperature is detected [12]. This approach requires one sophisticated and costly sensor for each cow.

In this work we propose a mastitis detection system based on the measuring of the EC of each quarter. The system is composed by one measurement unit (MU) per milking unit

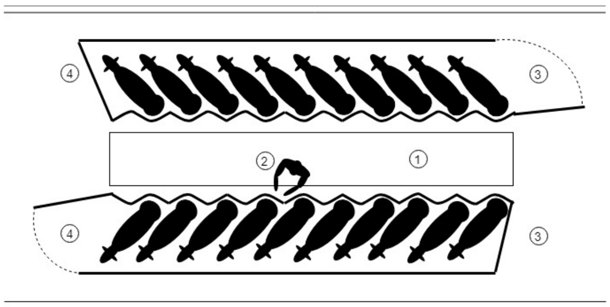


Fig. 1. Typical herringbones parlour and its parts: (1) operator's pit, (2) operator, (3) entry and (4) exit gate.

that measures EC and sends the values to a central unit (CU). Once the CU has the complete milking time series, the cow is classified. For that it is used a Random Forest approach to classify dairy cows in healthy and subclinical mastitis groups. The result of this classification is indicated by LED lights on the CU.

The rest of this paper is organized as follows. Section II describes the milking parlour. Section III presents the proposed system and its implementation. Section IV describes the method and circuits for milk conductivity measurements. Section V describes the implementation of the software for each component (MU and CU). Section VI introduces the machine learning techniques used for cow health classification. Section VII summarizes the experimental results obtained using the proposed system. Finally, Section VIII presents the conclusions and future work.

II. Milking parlour

The aim of the work is to develop a system able to be integrated in most adopted modern milking parlours. A representative milking parlour is described in the next section to later describe the proposed mastitis detection system.

Herringbone parlour has become popular in all major milk producing countries, since are suitable for medium to large herds (about from 50 to 400 cows). In this parlour cowshed stall are arranged in two rows at both sides of the operator's pit. Cows enter and leave in batches. In each row, cows stand in echelon formation at an angle of 30°-35°. There is one milking unit for each pair of stall, milking a row of cows at a time. Fig. 1 depict a herringbone parlour and its main components.

The operator most of the time is in the operator's pit milking and controlling the entry and exit of cows. He or she prepares the udders for milking and attach the teatcup clusters to them. During milking, the operator should check that every teatcup remains adjusted correctly. Modern milking machines are equipped with milk flow detectors to sense the end of milk flow to remove the cluster from the udder.

The milking cluster consists of four sets of teatcup, each of which has a shell and a rubber liner. The teacups are connected to vacuum by rubber tubes and claws to extract the milk. The milk travels from the teatcups through the short milk tubes to the claw, and later travel along the long milk tube to the bulk tank. The claw is made of stainless steel or combining parts of plastics and stainless steel, with a effective claw bowl volume about 200 ml.

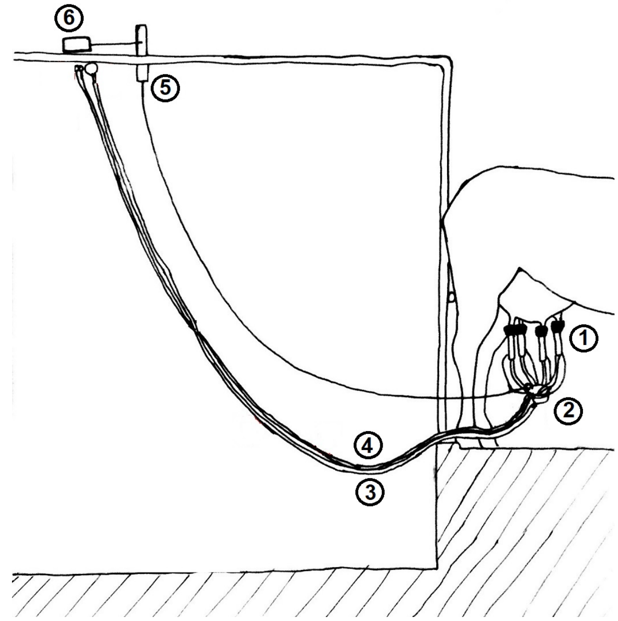


Fig. 2. Stall milking parlour: (1) cluster teatcup, (2) milking claw, (3) long tube, (4) vacuum tube, (5) automatic cluster removal mechanism (6) power cable tray

Fig. 2 depicts one stall milking parlour and the aforementioned parts.

III. Mastitis detection system

The system is composed by one MU per milking unit and a single CU. The MU is responsible for measure the milk conductivity per quarter and mix temperature and transmit them to the CU, which is in charge of analyzing the time series to determine if the cow has mastitis or not.

A. Measurement unit

The MU, depicted in Fig. 3, comprises a microcontroller, a Bluetooth (BT) radio transceiver, and four conductivity sensors and a temperature sensor for measuring the milk conductivity of each quarter and the temperature of the mixed milk respectively. A power supply subsystem feeds the modules with the corresponding voltage: ± 5 V, ± 12 V and 8 V dc source. Since, this unit is fed from the mains supply, no special power consumption optimization are considered.

The MU is split into two parts: one integrated into the milk cluster comprising the conductivity traducers and the temperature sensor, and another part with the measurement and auxiliary electronics circuits, the microcontroller and transceiver installed in the power cable tray. Fig. 3 shows a block diagram of MU.

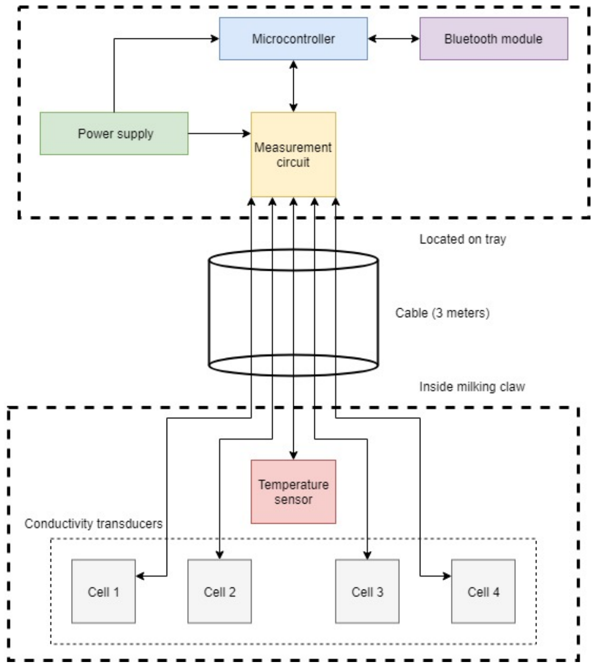


Fig. 3. Block diagram of the measure unit

1) Microcontroller: The microcontroller requirements include: i) two analog inputs, one for the conductivity sensor and another for the temperature sensor, ii) six digital output, two for the LEDs, three to control the conductivity sensor and one for the serial communication interface (UART port, Tx pin) for communicating with the Bluetooth module, and iii) one digital input for communicating with the Bluetooth module (UART port, Rx pin). An Arduino UNO module is selected because it is an excellent choice for prototyping. This module is powered from 8 V provided by the power subsystem.

2) Bluetooth: We considered a number of options for the wireless communication between the MUs and the CU. The Bluetooth technology offers a very good trade-off between cost, communication range and ease of use. The Bluetooth radio transceiver module selected is a HC-05 mainly because is a popular shield for Arduino with a communication range between 5 and 10 meters. The HC-05 supports serial communication (UART) and an AT command mode. The connection between the microcontroller, powered from 5 V, and the HC-05, powered form 3 V, is done using a voltage divider in the direction to the HC-05. The signal voltage from the HC-05 is within the tolerable input ranges of the microcontroller.

3) Temperature sensor: The temperature sensor selected is the LM35 [13] in a plastic TO-92 transistor package. The sensor features a typical accuracy of 0.75°C over a temperature range of -55°C to 150°C. The output voltage of the sensor is linearly-proportional, 10 mV/°C. Since the milk temperature is around 33°C and that it is expected to vary just a few grades, the sensor output is feed to an amplifier stage to reduce the quantization error at the microcontroller analog input. The temperature value is used to compensate the conductivity measurement.

4) Conductivity sensor: The conductivity sensor is specially developed for this particular application and it is described in Section IV. First, the design and implementation of conductivity traducer, which is the part of MU integrated into the milk cluster (upper part in Figs. 3), is described in detail. Then, the electronic circuits for signal conditioning is presented (lower part in Figs. 3).

B. Central unit

The CU is implemented using a Raspberry PI 3 platform. It features a quad-core 64-bit ARM Cortex A53 running at 1.2 GHz, Bluetooth 4.1, WiFi, four USB ports and an Ethernet port. It is selected because, it is a powerful single-board computer at a very low cost (around 35 US dollars). Since, it runs a linux-based operating system, Ubuntu Core 16 for Raspberry PI 3, it supports Python, which enables to use the classification libraries provided by scikit-learning (a Python based tool for data analysis).

IV. Conductivity measurement

The conductivity transducers requires measuring the milk conductivity of each quarter independently. The milk conductivity is within the range 1.0 mS/cm to 12.0 mS/cm, where lower values, close to 1.0 mS/cm, corresponds to a cow without mastitis [14].

To achieve this without modifying significantly the milk cluster, the transducers must be located inside the milk claw, which is relatively small (a few tens of cm^3 of available space). For a simple integration of these traducers, the designed electronic circuit presents a voltage output, which is easily acquired by an analog-to-digital converter (ADC) of the microcontroller. Moreover, the conditioning circuit is shared between quarters to reduces cost and size. An enable signal is used to initiate a measuring, plus two additional digital signals to select the quarter.

A. Cells modeling and design

The conductivity of a solution retained in a vessel or cell can be measured based on Ohm's law by applying an alternating electrical current to two opposite surface electrodes located parallel to each other and measuring the resulting voltage. The expression for the resistance of the solution is

$$R_m = \frac{l}{\sigma A}. \tag{1}$$

Thus, the conductivity can be obtained using

$$\sigma = \frac{K_{cell}}{R_m}, \tag{2}$$

where K_{cell} is the ratio of the distance between electrodes, l , and its area, A. If this cell constant is computed geometrically may be subject to errors and it should be better determined by calibration using standard solutions. Alternate current is used to avoid polarization effect, accumulating ionic species near the electrodes, leading to erroneous results as it adds a parasitic component to the solution resistance.

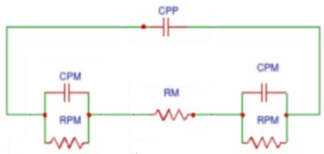


Fig. 4. Equivalent-circuit model.

TABLE I
EQUIVALENT CIRCUIT MODEL VALUES.

R_m (Ω)	C_{pm} (pF)	R_{pm} (Ω)	Cpp(pF)
688.4	63.8	3.4	100.0

In order to identify the effects of the cell geometry and other factors on the milk impedance, a lumped-element equivalent circuit model is used.

First a reference cell is build, a cube with the sides of 1 cm. The impedance of this cell filled with a KCl solution of 1.3 mS/cm at 19°C is acquired using the impedance analyzer Cypher Instruments C60. Various RLC circuits are tested, fitting the measurement data to the model in the range of 1 kHz to 100 kHz. The adopted model is depicted in Fig. 4, where: R_m is the milk resistance, used to determine the conductivity using Eq. (2); C_{pm} and R_{pm} represent the capacitance and resistance of the milk electrode (plate) interface respectively in series with the milk resistance; and finally C_{pp} models the capacitance between electrodes. Compared to previous models (e.g. Mabrook et al. [15]), the proposed one adds the R_{pm} for a better fitting, modeling the resistance in the milk-to-electrode interface. The data is fitted to the model using a nonlinear least-squares solver in Matlab.

Fig. 5 shows the impedance (module and phase) of the reference cell, measured and modeled, and Table I shows the model component values after the fitting.

The effects of the capacitance C_{pp}, in parallel with the branch of R_m, are significant for frequencies higher than 100 KHz. While the impedance of the milk-to-electrode interface (parallel of R_{pm} and C_{pm}) are negligible for frequencies higher than 10 KHz. Moreover, it can be observed that the phase is almost zero for a frequency slightly higher than 10 KHz, so that $|Z| \simeq Re(Z)$. Since, $R_m \gg R_{pm}$ then $|Z| \simeq R_m$. Therefore, a frequency of 10 KHz is adopted for the measurement current, since it allows measuring with relative ease $|Z|$ to estimate with low relative error R_m. The measurement method is explained in Section IV-C.

Two more cells are built varying its size and characterized finding the parameters values of the equivalent circuit. The obtained results confirm that the model is correct for modeling the dependence of the main parameters with the dimension of the cell (R_m is proportional to the distance between electrodes and inversely proportional to its area, the opposite is valid for C_{pp}). It is found that the reference cell is the most appropriate cell, presenting a good trade-off between reduced size and low relative error.

The milk conductivity also depends on the temperature.

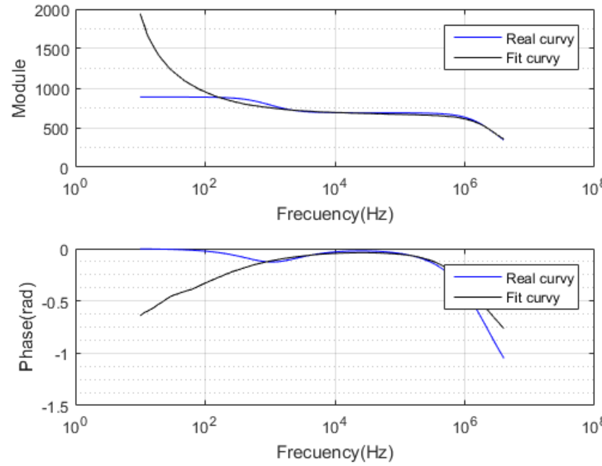


Fig. 5. Impedance (module and phase) of the model and experimental data.

Fig. 6. Milking claw.

The mobility of the ions increases with the temperature, so the conductivity increases. To compensate this effect, the following formula is used [4]:

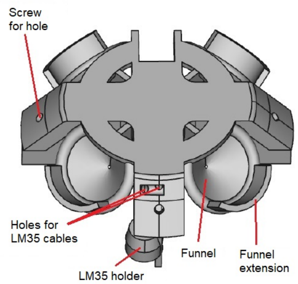
$$\sigma = \sigma_0 \left(1 + \alpha(T - T_0)\right) \tag{3}$$

The parameter α is determined obtaining conductivity measurements for three temperature values. It is verified that the correction is relative small, 2.4 $\%/°$C and consistent with previous reports [4].

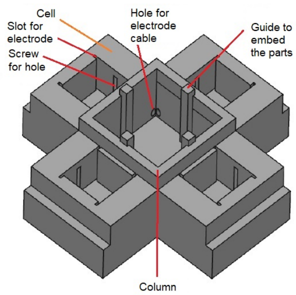
B. Mechanical design

The conductivity cells, defined in the previous section, and the temperature sensor must be integrated into the milking claw (see Fig. 6). The designed piece consists of two parts: i) the upper support part, which is attached to the milking claw with screws, and ii) cells part. The design is made in two parts to make its manufacture feasible using a 3D printer. The design is done using the FREECAD's software. Fig. 7 shows a perspective view of both pieces.

The upper support has four funnels (one per cell) to reduce the milking flow and force them to be stationary, so that the EC measurement can be accurate (otherwise, it is affected by



(a) Upper support



(b) Cells

Fig. 7. Design of pieces to put in the milking claw.

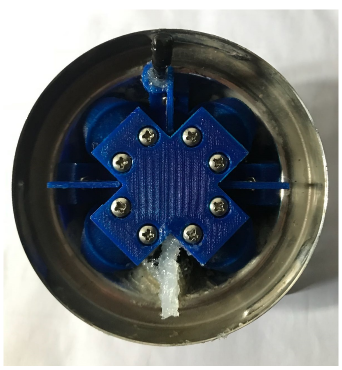


Fig. 8. Pieces attached to the milking claw.

turbulences). Both pieces are sticked together using acrylic glue.

It is used two stainless steel electrodes with an effective area of 1.0 cm^2 and 1 cm apart. They are attached to the cell with steel screws. Fig. 8 shows a photograph of the final piece attached to the milking claw.

C. Electronic design

Fig. 9 shows a block diagram of the EC electronic circuit. Implementation details are omitted due to space restrictions. The alternating voltage, necessary to measure the EC, is generated with the oscillator block. This is composed of a LM555, which generates a periodic square wave, and a band pass filter to obtain a sinusoidal voltage. The filter is designed to pass the fundamental harmonic of the square wave and reject all the other harmonics. The filter gain adjusts the output of the oscillator block to an amplitude of 1.0 V. The sinusoidal signal from the oscillator block is feed to one cell to

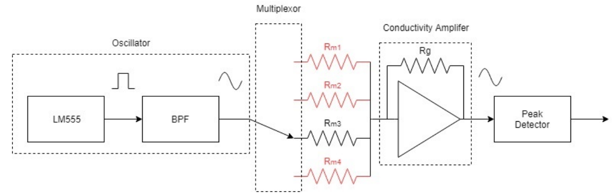


Fig. 9. Block digram of the EC electronic circuit.

measure its EC . This is done using a multiplexer (ADG1604) with four channels. The cells are represented as electrical resistance R_{mi} (where i identifies the cell: from 1 to 4) in the diagram. The voltage drop of the selected cell is connected to an operational amplifier (OPA4192) in inverse configuration with gain R_g/R_{mi}. So, the output voltage amplitude of the amplifier is inversely proportional to the milk resistance, so it is proportional to the EC. The final step of circuit is a peak detector to obtain from the ac signal its amplitude value. The output of the described electronic circuit is a voltage signal proportional to the EC of the selected cell. Assuming each block as ideal, the circuit's transfer is:

$$v_{cond} = \frac{R_g}{K_{cell}}\sigma_m \tag{4}$$

D. Calibration

The conductivity output voltage is acquired by the ADC of the MU microcontroller and sent to CU. The CU convert the received raw value (a number from 0 to 1023) to a conductivity value (mS/cm) using a linear relationship, $y = ax + b$, where the b coefficient accounts for off-set errors . For this conversion the parameters of a transfer function must be calculated previously. The gain of the Eq. (4) can be calculated using the nominal values of the electronic components and the cell dimensions to calculate its constant (offset zero is assumed). Another way to determine them is through a calibration procedure, fitting data samples to a curve using least squares regression. There are two options for calibration, obtaining: i) an individual curve per cell, and ii) an unique curve corresponding to an *average cell*, in which the four cell acquired values are considered for each solution. Five different NaCl solutions in the range 1.0-12.0 mS/cm are prepared. The EC of these solutions are measured using a commercial conductivity meter (Goodes TDS&EC E-1 Portable) and the output voltage of the conductivity sensor saved for further processing.

Fig. 10 shows the data samples corresponding to the four cells for each solution and the obtained curves. Clearly, the calibration curve for each individual cell are different. This may be explained by the differences between electrodes that are made manually, so their electrical characteristics are different. Also it can be observed that the offset is negligible.

The error (E) is computed with the following expressions [16]:

$$E = 100 \times \frac{y_{error}}{y} \tag{5}$$

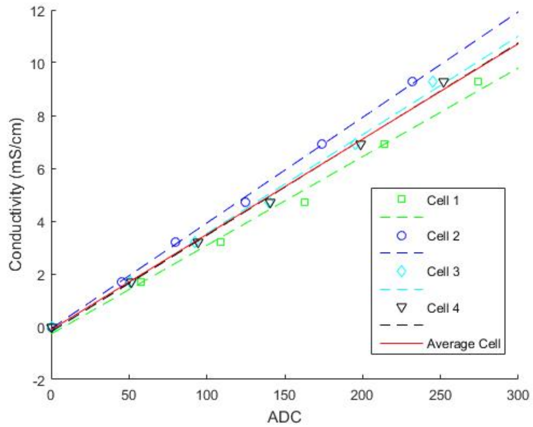


Fig. 10. Calibration curve for each cell.

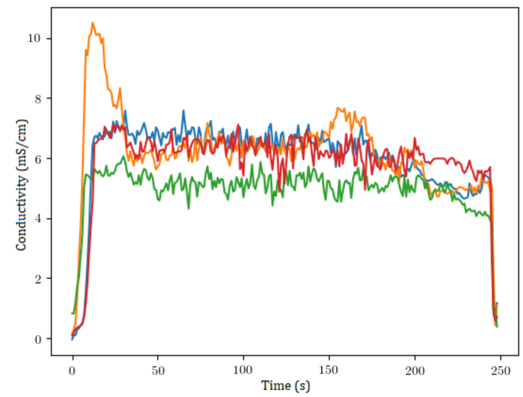


Fig. 11. EC time series of a infected cow with a SCC of 3.399.000 cells/ml.

and

$$y_{error} = t_{\alpha/2,n-2} \cdot S \cdot \sqrt{\frac{1}{n} + \frac{n(x - \bar{x_i})^2}{n\Sigma x_i^2 - (\Sigma x_i)^2}} \tag{6}$$

where x is the value at which the error of the result y is estimated, x_i are the samples used for calibration, n is the quantity of samples, $\bar{x_i}$ is the average of samples, $t_{\alpha/2,n-2}$ is the critical value of normal distribution ($\alpha = 0.05$) and S is the standard deviation of the samples.

Table II presents the maximum error throughout the range of interest for each calibration procedure. The table shows that the error using the nominal transfer function has a higher error, and that the the *average cell* has the lower error than individual curves, but just because it has more samples (see Eq. (6).

TABLE II
CALIBRATION PROCEDURE ERROR

	C1	C2	C3	C4	avg.	nom.
Error (%)	13	11	12	12	6	14

V. IMPLEMENTATION

This section discuss the software implementation of the MU and CU. MU has the following tasks: i) sampling the EC of each cell with milk and the temperature of the milk's mix, ii) sending and receiving data through Bluetooth network, and iii) displaying ubber' state information through LEDs. MU samples the analog input and selects a new cell each 250 milliseconds, so one time per second all the cells are sampled. Once the four cell are sampled, it is sampled the temperature. Finally, the measurements are sent to the CU using Bluetooth for processing.

On the other hand, CU is waiting for a new packet from the MU. Once a new packet is received, it decides if the data corresponds to the time series of the current cow, to obtain separated data series for each one. Fig 12 shows the decision tree for a new data arriving to the CU, explained next. A new

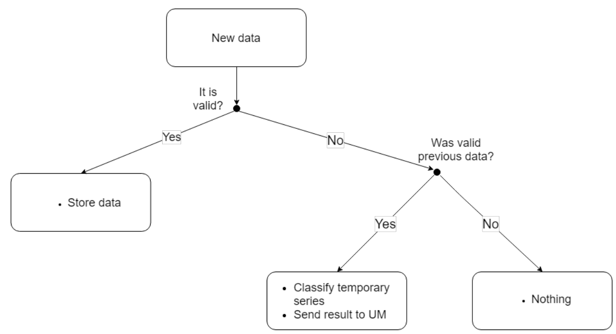


Fig. 12. Decision tree for a new data arrived to the CU

data belongs to the current milking if the mean of the last 10 samples of each quarter is higher than a fixed threshold. In this case, the data is saved.

If the data don't belong to the current milking, means that the milking has finished and the time series of the cow is analyzed and the result is sent to the MU.

Fig. 11 shows the four time series of a milking, where it can be observed that between milking (different cows) the EC drops considerably.

The complete system will integrate automatically information of caws. Each caw will be identified using a RFID reader that scan the cow ear tag as enter to the parlour though the entry gate. This ID is used to identify the cow with the EC's time series. With this ID, it is possible applying post-processing techniques to the data using extra information of the cow (age, number of health quarter of the udder) to improve the classification model. For this purpose, this prototype uses a mobile app to manually enter the cow ID. The communication between the CU and the app is via Bluetooth.

VI. CLASSIFICATION

This section explains the classification model and which characteristics are extracted from the EC's time series.

First, the following terms related to classification techniques are defined in the problem domain:

- TP: correctly classified mastitis cases (true positive)
- FP: misclassified healthy cases (false positive)
- FN: misclassified mastitis cases (false negative)
- TN: correctly classified healthy cases (true negative)

The performance of the classification is evaluated employing:

- positive predictive value (PPV) or precision,

$$PPV = \frac{TP}{TP + FP},$$

- true positive rate (TPR), sensitivity, or recall

$$TPR = \frac{TP}{TP + FN},$$

- true negative rate (TNR) or specificity

$$TNR = \frac{TN}{TN + FP}, \text{ and finally}$$

- F1-score

$$F_1 = 2 \cdot \frac{PPV \cdot TPR}{PPV + TPR}$$

In order to obtain a database for training purposes, an operational prototype of the system is installed during several days in a parlour of a dairy farm near Florida (80 km apart from Montevideo, Uruguay). The database contains 95 samples, where 63 samples are labeled as healthy and 32 samples are labeled as infected samples (cases of mastitis). Each sample has the four EC quarter milk time series, number of birth and percentage of grass and protein of the mixed milk. Milk samples are extracted and analyzed to determine the state of health of the cows. A database sample is labeled as infected if SCC is higher than 400.000 cells/ml. Fig. 11 show the EC of milk of a infected cow.

We evaluated for the classification the four characteristics used by Norberg et al. [7] which are extracted from the each EC quarter milk. The average of the 20 highest valid EC measure within a milking (X_20) and the variation of all valid EC measure within a milking (σ^2_{EC}) are calculated for each quarter. The following EC characteristics are computed: MAX_X_{20} (the highest quarter X_{20} value within cow and milking), $MAX\_\sigma^2_{EC}$ (the highest quarter σ^2_{EC} value within cow and milking), IQR_X_20 (the inter-quarter ratio between the highest and lowest quarter X_{20} value within cow and milking), and $IQR\_\sigma^2_{EC}$ (the IQR between the highest and lowest quarter σ^2_{EC} within cow and milking). It is also used as characteristics: milking duration, number of quarter milking (sometimes the four tits are not milked) and percentage of grass and protein of the milk.

The classification method adopted is Random Forest algorithm. In fact, this algorithm is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting.

The dataset is evaluated using cross validation techniques to optimize the model. It is used F1-score, recall and precision for the model evaluation defined previously. Table III shows the result when only one of the characteristics is used for classification. Table IV shows the obtained the result when combining the characteristics in three subsets:

TABLE III
CROSS VALIDATION IN 10 FOLDS

	F1	**Precision**	**Sensitivity**
Max_X_{20}	46.63± 2.84	43.78±3.42	50.00±2.98
$Max\_\sigma^2_{EC}$	**64.19±2.11**	**65.07±2.67**	**63.46±3.10**
IQR_X_{20}	36.42±3.77	34.65±3.096	38.46±4.87
$IQR\_\sigma^2_{EC}$	35.09±2.16	33.18±2.32	37.31±2.46
$Nro.\ quarter$	11.00±6.00	30.86±15.00	7.30±4.01
$Grass$	44.14±2.44	44.87±2.67	3.46±2.46
$Protein$	19.09+3.66	18.63±3.43	19.62±4.02
$Duration$	54.93±4.11	54.93±4.85	55.00±3.86

TABLE IV
CROSS VALIDATION IN 10 FOLDS. COMBINING CHARACTERISTICS.

	F1	**Precision**	**Sensitivity**
all	42.66±2.05	55.90±5.00	3.62±2.30
best3RF	45.66±4.76	50.03±4.92	37.31±4.57
Norberg	37.88±2.50	41.47±2.87	35.00±3.19

- all: all the characteristics together.
- best3RF: using only the three best characteristics selected by Random Forest.
- Norberg: using only the characteristics extracted from [7].

It can be observed from Table III, and Table IV that the best option is $Max\_\sigma^2_{EC}$ (highlighted in bold) obtaining a F1-score of 64%, a precision of 65% with a sensitivity of 63%.

VII. CONCLUSIONS

We have presented a mastitis detection system based on the measuring of the electrical conductivity of each quarter milk. The proposed solution can be adopted in virtually any milking parlour machine since it requires only to substitute the milking claw. The developed milking claw includes four cells to measure in real time the electrical conductivity of the milk of each quarter udder. The MU can be placed near the corresponding stall which send wirelessly the measurements to the CU. Once the milking of a cow is finished, the data is processed by the CU to determine whether the cow has mastitis or not. This information is sent back to the MU to properly alarm the operator if he or she needs to take an action.

A operational prototype composed of one MU and the CU are successfully tested on field. The classification performance is well in line with the best mastitis detection systems reported up to date in the literature. Best results is obtained using the $Max\_\sigma^2_{EC}$ as characteristic in which the validation shows a specificity of 83.20%, a sensitivity of 63.46 % and a predictability of 65.07 % for infected cows. This result seems to indicate that it is possible to use the system to make a shortlist of the infected cattle to be trait for the veterinary technician.

Table V shows a comparison with other works in which the cattle have similar characteristics to ours.

Norberg et al. [7], [9] obtained similar specificity but a lower sensitivity and predictability for infected cows. Both works developed inline system where EC of quarter milk is

TABLE V
COMPARING RESULTS WITH OTHER WORKS.

	Sensitivity	**Precision**	**Specificity**
This work	63.46	65.07	83.20
Norberg et al. [7]	44.80	–	84.60
Lien et al. [9]	46.20	30.70	83.70
Cavero et al. [8]	70.00	–	84.00
Biggadike et al. [6]	50.00	48.00	87.00

measured without using historical data. The best result are obtained by Cavero et al. [8], which is reasonable because in their work it is used historical data from EC quarter. Finally, Biggadike et al. [6] in which also used historical data, obtain a better specificity but worst predictability for infected cows and sensitivity. In our work, once the equipment is installed and working, these data could be incorporated and the classification model retrained.

The future work includes the design for manufacturability of piece of the cell, improving the electrode's building process and using an appropriate material for plastic piece that resist cleaning products used at the parlour.

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