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Sensor networks

Digital Moka: Small-Scale Condition Monitoring in Process Engineering

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Abstract—In this letter, we present a data-driven condition-monitoring system for a moka pot aiming at anomaly detection in the coffee-preparation process. A data-acquisition system and the corresponding generation process of a comprehensive dataset (including data from ideal and anomalous brewing scenarios) are described. Supervised and unsupervised machine learning algorithms are trained and tested on the dataset aiming at detecting anomalies in the process and showing the relevance of the considered framework.

Index Terms—Sensor networks, anomaly detection, condition monitoring, digital twin, moka pot, process engineering.

I. INTRODUCTION

Digital twins represent a crucial tool for monitoring purposes in many relevant domains (e.g., manufacturing, energy, maritime, transport, health) [1]. Their success rely on the availability of real-time real-world data coupled with the capability of advanced data processing (e.g., based on machine learning tools). Although no general agreement is found, some general steps for the implementation of digital twins may be identified [2]: data acquisition system (DAS) with a wide variety of sensors; communication channels between physical and virtual domains; data collection, formatting and storage; advanced analytics tools; data visualization, understanding and interpretation; action feedback to the physical system. Condition monitoring and fault detection are key functionalities within digital twins [3], [4].

The moka is one of the most popular instruments to brew coffee.[1] Coffee preparation with a moka is a complex thermodynamic process whose output greatly depends on multiple parameters (i.e., heat supply, initial water content, initial coffee weight): Variations in any of these parameters have considerable impact on the coffee quality. The presence of anomalies and the easiness in data generation, makes the moka an interesting candidate to run experiments mimicking condition monitoring in process engineering. The digital moka has potential to provide insights about several issues related to Industry 4.0.

The moka structurally consists of two chambers: the lower boiler chamber, which holds the water before the brewing process and the top chamber, which holds the coffee after the brewing process. A funnel equipped with the filter plate fits snugly into the boiling chamber and then the top chamber is screwed onto the boiler chamber. The length of the funnel is such that it does not touch the base. The boiler has a pressure release valve for safety purposes and the top chamber has a spout through which the coffee flows. The coffee-preparation process consists of the following steps:

1) The bottom chamber is filled with water such that that safety valve is not covered (a reference line is usually present).
2) Coffee grounds are poured into the funnel and loosely packed (overfilling must be avoided; grinds cannot be too fine).
3) The top chamber is fixed onto the lower chamber creating a tight seal (steam escapes should not happen).
4) A consistent medium heat is supplied to the the pot till enough pressure is created for the water to flow from the bottom chamber, through the funnel and wet the coffee grounds.
5) The process continues until the coffee starts flowing consistently through the spout into the top chamber (until some residual steam passes through the spout, marking the end of the process).

The available literature on the analysis of the moka is very limited with a few experimental works [6]. A theoretical formulation of the coffee-brewing process is based on Darcy's law of linear filtration to explain the pressure required by the water to pass through the coffee grounds [7]. An experimental setup with two thermocouples, i.e., one in the spout and one inside the boiling chamber, focused on physics-based analysis via estimation of the filtration process and coefficient [8]. The strength and taste of coffee have been shown to depend on the duration of contact between the water and coffee grains, the pressure and the temperature at which the extraction happens, and the coffee grain size [9], [10]. One work (setup with 12 thermocouples, one pressure sensor, and one level detection circuit) highlights the need for collecting the temperature at various locations [11]. Dry air in the boiling chamber plays a key role in the brewing process, which is analyzed in two phases: *Regular Extraction Phase*, with smooth and consistent flow of the coffee into the top chamber; *Strombolian Phase*, characterized by immense evaporation and gurgling sound.

The main contributions of this work are the following:

1) exploring data-driven techniques for innovative design of a moka-pot digital twin;
2) presenting ***DigiMoka***, i.e., a dataset made of 64 realizations of a multivariate time series from temperature and pressure sensors;[2]

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[1] Approximately 90% of the households in Italy use "Moka Express" by Bialetti [5].

[2] Dataset publicly available at http://folk.ntnu.no/salvoros/DigiMoka/

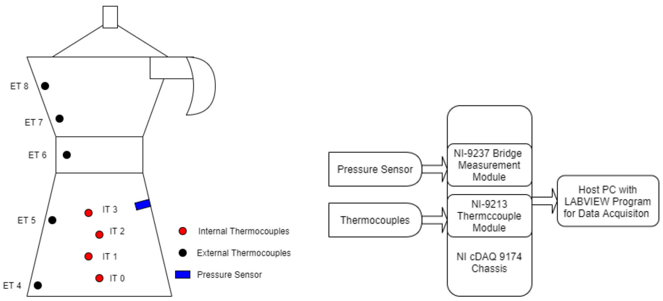


Fig. 1. Location of the sensors on the moka pot (left) and DAS (right).

3) assessing the performance on the considered dataset of classical tools for anomaly detection and classification.

This letter is organized as follows: Section II describes the DAS considered for the experiments; DigiMoka is described in Section III; Section IV presents the results of some techniques for anomaly detection applied to DigiMoka; finally, in Section V concludes this letter.

II. DAS

We used the 12-cup version of the "Moka Express" by Bialetti. The DAS was inspired from [11] and based on collecting information about the temperature on the surface of the moka, the internal temperature of the moka and the pressure inside the boiling chamber. More specifically, five external temperature sensors, four internal temperature sensors, and one pressure sensor were placed, as shown in Fig. 1. Sensors were interfaced with equipment from National Instruments and a Labview virtual instrument was created to handle the data, including syncrhonization, and produce CSV files accordingly.

The setup (block diagram shown in Fig. 1) is described here.

1) The Moka Express from Bialetti Industries is among the most popular. A 12-cup moka was chosen for easy application of sensors. The boiler capacity is 775 ml and one pot typically produces 12 shots (1 shot contains 30 ml of coffee).
2) An electric kitchen stove was used as heat source with multiple heat levels, thus allowing data generation with different settings.
3) Thermocouples for external temperature were of type-T (with junction made of copper-constantan). Their range is (-270 °C, $+370$ °C). Thermocouples for internal temperature were of type-K (with junction made of nickel–chromium and nickel–Alumel). Their range is (-270 °C, $+1260$ °C).
4) NI-9213 is a data acquisition device (with 16 independent channels) specifically designed for thermocouple signal conditioning. It operates at 1 sample/s (high resolution mode) or with a maximum sample rate of 75 samples/s (high speed mode). The NI-9213 module provides cold junction compensation internally and the typical error in temperature measurement within the range (0 °C, 200 °C) degrees is ± 1 °C for both types of thermocouples.
5) The pressure sensor used in the experiment belongs to the XTME-190(M) series, produced by Kulite. This transducer can be safely used in temperatures up to 232 °C and pressures up to 5000 psi. It has a piezoresistive element to change its resistance according to the pressure applied.
6) NI-9237 Bridge Measurement Module (with four channels and a sample rate of 50 000 sample/s per channel) was used to measure the pressure from the transducer. The typical error in measurement is rated at 0.2% of the reading.
7) The NI cDAQ-9174 chassis enables the use of multiple data acquisition modules and connects to a single USB port on the host PC. It provides features for triggering/synchronization between the modules attached to the chassis. It provides digital routes for managing the data flow from the modules to the host PC.

III. DATASET

Preparation of coffee with a moka pot has many process parameters, the process is not standardized, and an ideal cup of coffee is a subjective definition depending on individual preferences. We focus on "water quantity" (real-valued variable), "coffee-grind weight" (real-valued variable), "heat supply" [discrete variable, we consider three possible values: *consistent medium supply* (CMS), *consistent high supply* (CHS), *inconsistent supply* (IS)], and the sealing condition of the pot identified through the "leak fault" (binary variable).

More specifically, we identify seven different scenarios: normal conditions (NC), insufficient water (IW), insufficient coffee (IC), high heat (HH), inconsistent heat (IH), leak fault (LF), sensor fault (SF). The first scenario (i.e., NC) is assumed without any anomaly, while each of the remaining six scenarios exhibits a single anomaly with five anomalous scenarios related to the parameters previously identified, and one (i.e., SF) to an artificial sensor failure[3] identified by the "sensor fault" (binary variable). In this work, we do not consider multiple simultaneous anomalies. Table 1 shows the information related to the parameters within each of the seven scenarios, including the number of runs (a total of 64 runs were performed).

Data were sampled at $f_s = 50$ Hz. Fig. 2 shows three examples of sensors' measurements (each example from a single run) for three different scenarios, in order to highlight the different pattern in the corresponding multivariate time series. More specifically, it is apparent how the IT3 sensor and the pressure sensor exhibit significant deviation in the case of IW scenario and LF scenario, respectively, with respect to the corresponding measurements in the NC scenario. Some other anomaly scenario may present different patterns, which are less apparent through visual inspection. Also, it is worth noticing that the total duration of each single run is quite similar in each scenarios; however, the average duration for IW, IC, HH, IH scenarios (resp. LF scenario) is significantly smaller (resp. larger) than the average duration for NC and SF scenarios (the last two are apparently similar).

IV. ANOMALY DETECTION AND PERFORMANCE

Feature extraction is a preprocessing technique used to reduce the amount of data to be processed and related processing time. Domain experts can identify relevant features and represent the same information in a lower dimensional space with negligible degradation. The following features were considered as an alternative to raw sensor data: *Total Duration* (i.e., the total time of the single run); *Brew Start Time* (i.e., the time at which the water enters the coffee chamber[4]); *Brew Duration* (i.e., the time duration from the brew start time till the end of the run); *Maximum Pressure* (i.e., the maximum pressure reached for the single run); *Maximum Internal Temperature* (i.e., the maximum temperature inside the boiling chamber for the single run).

Two different tasks were assumed in our analysis as follows:

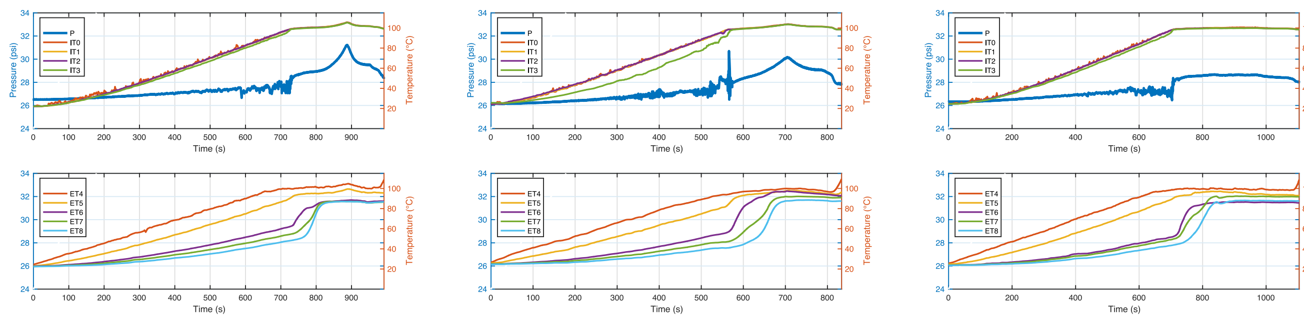
1) "Detection," i.e., detect if the process experienced NC or not;
2) "Classification," i.e., identify which scenario was experienced.

[3]One of the external temperature sensors was intentionally detached and reattached during the brewing process.

[4]Computed by differentiating data from ET6 and applying a threshold detector.

Table 1. Parameters Used in Different Scenarios.

parameter/scenario	NC	IW	IC	HH	IH	LF	SF
Water quantity ($m\ell$)	630 – 640	< **550**	630 – 640	630 – 640	630 – 640	630 – 640	630 – 640
Coffee-grind weight (g)	45 – 50	45 – 50	< **30**	45 – 50	45 – 50	45 – 50	45 – 50
Heat supply	CMS	CMS	CMS	**CHS**	**IS**	CMS	CMS
Leak fault	no	no	no	no	no	**yes**	no
Sensor fault	no	no	no	no	no	no	**yes**
# of runs	40	4	4	4	4	4	4



(a) (b) (c)

Fig. 2. Examples of measurements under different scenarios. (a) NC scenario. (b) IW scenario. (c) LF scenario.

Four different techniques (three unsupervised approaches and one supervised approach, which exhibit different performance and complexity) for anomaly detection were applied on each task: 1) *Univariate K-Means Clustering on pressure data*, 2) *Univariate Hierarchical Clustering on pressure data*, 3) *Univariate Nearest-Neighbour (NN) Classifier on each sensor data plus Majority Voting (MV)*, and 4) *Support Vector Machine (SVM) Classifier on features*. The Euclidean distance was used for all the clustering algorithms.

A. Algorithms

K-Means Clustering. It is based on an iterative procedure alternating the assignment of data points to the closest cluster center and the update of cluster-centers based on centroids. The K-Means clustering algorithm was applied on *raw pressure data*, where all the time series were made into equal length via zero-padding at the end of each run. It is worth noting that $K = 2$ (resp. $K = 7$) cluster centers were used for detection (resp. classification).

Hierarchical Clustering. Clusters may be built in a hierarchical fashion proceeding top–down by splitting large clusters (divisive approach) or bottom–up by merging similar clusters (agglomerative approach). Agglomerative hierarchical clustering was applied on *raw pressure data*, where all the time series were made into equal length via zero-padding at the end of each run.

NN Classifier With MV. NN Clustering is based on selecting the class of the closest training example. One univariate NN classifier was built for each single sensor and based on *raw sensor data*. MV among the individual decisions of the univariate classifiers was then used for the final decision [12]–[15].

SVM Classifier. The algorithm looks for optimal hyperplanes in order to partition the input space into subsets associated to the classes. It builds upon binary classification, where a hyperplane is found via class-distance maximization, by using strategies like 1-vs-1 approach. An SVM classifier is trained for each pair of classes using *described features* as input, and all the binary classifiers participate in a voting strategy during the test phase. The input data are mapped via a nonlinear mapping (a radial basis function is assumed) into a higher dimensional space to facilitate hyperplane-based class separation.

Table 2. Detection Performance.

method/performance metric	Accuracy	Precision	Recall
K-Means Clustering	0.85	0.79	0.75
Hierarchical Clustering	0.87	0.83	0.75
Univariate NN Classifier with MV	0.85	0.82	0.70
SVM Classifier	0.88	0.93	0.70

Table 3. Classification Performance.

method/performance metric	Accuracy	Precision	Recall
K-Means Clustering	0.62	0.44	0.49
Hierarchical Clustering	0.40	0.44	0.47
Univariate NN Classifier with MV	0.83	0.78	0.70
SVM Classifier	0.87	0.78	0.78

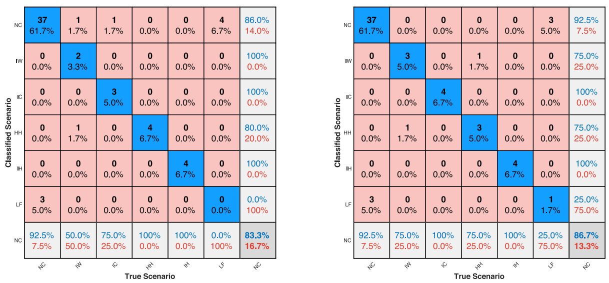
B. Discussion

Given the limited amount of data, the leave-one-out cross-validation method is used for performance assessment,[5] i.e., one single run is considered as test set, and the remaining runs are used for training the model. The procedure is repeated to have each run selected once as test set, and average performance on the test examples are computed.

Performance for both detection and classification tasks is measured through *accuracy*, i.e., the ratio between the number of correct predictions and the total number of predictions, *precision*, i.e., the ratio between the number of correct predictions within the generic class and the total number of predictions in that class, and *recall*, i.e., the ratio between the number of correct predictions within the generic class and the total number of examples from that class. In the case of unsupervised methods, the labels were used for evaluation purposes (not for training) and the Hungarian method maximizing accuracy was used for optimum label assignments on clusters.

Tables 2 and 3 show the performance achieved by each method for each task. It is apparent how both unsupervised and supervised approaches achieve high performance for the detection task, with

[5]Results reported here do not include the SF class, because this kind of anomaly cannot be detected with the univariate approach.



(a) (b)

Fig. 3. Confusion matrices for two classifiers. Note that percentages refer to joint (not conditional) probabilities. Grey column and row represent class precision and recall, respectively. (a) Univariate NN classifier with MV. (b) SVM classifier.

the SVM detector slightly outperforming the unsupervised clustering algorithms. Things are different for the classification task, where the SVM classifier keeps similar performance as for detection, while the performance of unsupervised clustering algorithms degrade significantly. The reason for this severe degradation is found in the fact that while anomalous scenarios exhibit significant different patterns from the NC scenario, the differences between different anomalies is much weaker to be handled with unsupervised univariate clustering. The analysis of the dendogram in the case of hierarchical clustering (not shown here for brevity) clearly shows how the first layer separates RC and anomalous scenarios (thus the good detection performance), while proceeding deeper in the architecture the different anomalous scenario result mixed without any clear distinction for each scenario (thus the poor classification performance). The performance of the univariate NN classifier with MV shows a good balance between performance and complexity, proving that multivariate processing provides significant performance gain. Fig. 3 shows the confusion matrices for those two classifiers. Both methods experience similar misclassifications between NC and LF scenarios, while misclassifications among other pairs have different patterns.

Current results seem to indicate that pressure and internal temperature sensors are the most relevant; however, a robust analysis on the tradeoff between performance and number of sensors is beyond the scope of this work. Labeling appears a crucial information to perform high-accuracy classification.

V. CONCLUSION

We presented a DAS based on (internal and external) temperature and pressure sensors for condition monitoring of a moka pot. The goal is a data-driven anomaly-detection system for coffee-preparation as a small-scale process-engineering experiment. A dataset made of multivariate time-series for ideal and anomalous brewing scenarios was generated and described. Unsupervised clustering on raw data and feature-based SVM classifier were trained and tested. High detection performance are achieved by all the considered algorithms, while only the SVM classifier is able to keep high classification performance.

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