ChAALenge: An Ambient Assisted Living Project to Promote an Active and Health Ageing

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Abstract

The rapid growth of older population in the next years will lead to the rapid growth in the demand of health care, resulting in an increasing difficulty in managing hospitalizations and in a prohibitive grow of costs for medical care. In this context, chronic heart failure emerges as one of the most difficult problems to be treated, especially in advanced age, and a major cause of hospitalization and death. The Project ChAALenge aims at facing the problem by proposing a proactive approach based on pervasive monitoring and artificial intelligence. The goal is to promptly stepping, before the pathology onset, with effective suggestions ranging from the request of medical examination to the adjustment of lifestyle. The current paper presents the mid-term results of the ongoing project, introducing the sensors, the middleware and the candidate artificial intelligence techniques constituting the predictive system of the older adults' health status.

Keywords

Ambient Assisted Living, Health Monitoring System, Health Ageing, Anomaly Detection

1. Introduction

The EU 65 or more year-old population bracket is estimated to grow faster in the next years, if compared to the population bracket aged between 15 and 64 year-old, reaching the 50% in 2060. Since the health care demand grows with the age, according to the previous estimation it follows that such demand in the next years will grow proportionally [1]. In the plethora of diseases that can occur in a chronic form in the older population, heart failure is one of the major. Since its first methodical documentation in early nineties, heart failure has increased in the new century

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to become the more frequent cause of hospitalization and mortality in the ageing population [2]. The mean age and diagnosis is 76 year-old, and the percentage of incidence increases rapidly in the transition to old age. Specifically, incidence is 2% in people aged 40-59 years, 5% in people aged 60-69 years, and 10% in people with more than 70 year-old [3]. Despite the introduction of effective cures, the mortality rate still remains too high [4]. To date, heart failure is the cause of 20% recovery of more than 65 year-old, and the likelihood of death after the diagnosis goes from the 20% of the first year to the 50% over the next 4 years [5]. In Italy, the hospitalization for heart failure mainly involves older people, and it has been demonstrated that there is a progressive increase of hospitalization for people at high risk of developing chronic heart failure as they age [6]. Effective and efficient solutions to the problem stand on the promotion of a healthy lifestyle and an active and balanced ageing. However, classical health treatment are inadequate for the majority of older heart patients due to difficulties in constant monitoring, inadequate assessment of clinical profile, and poor communication between healthcare workers.

Recently, the American College of Cardiology and the American Heart Association published a series of guidelines for the evaluation and treatment of chronic heart failure [7]. They propose a four-stage classification approach, as follows:

- Stage A: high heart failure risk without apparent structural abnormalities of the heart.
- Stage B: structural abnormalities of the heart without past heart failure trauma.
- Stage C: structural abnormalities of the heart and current or past heart failure symptoms.
- Stage D: refractory symptoms to standard treatments.

Such classification highlights the need of large-scale treatment strategies to face the underestimation of the progressive nature of the heart failure as pathology related to advancing age. Fundamental requirement to pursue such goal is an integrated system capable of seamlessly monitoring and collecting vital parameters of the user. One solution is provided by the Care@Home methodology and the OMNIAPLACE [1] platform developed by eResult [8]. The project aims at implementing a highly specialized health care monitoring system capable of providing a customized mechanism of health status forecasting of older people, that enables technologies to undertake measures to prevent the onset of the disorder. The goal is to anticipate the heart failure onset by proactively providing to either the patient directly concerned, or his general practitioner, insights on the worsening of the patient's health status. The clues may highlight the need of specialized visits, suggest a change from a dissolute lifestyle to a healthier one, and so on. To allow *ad personam* solutions, the project introduces the concept of *virtual badge*, which consists in an highly customized profile of the patient built on data collected by sensors. The Project ChAALenge aims to evolve the Care@Home methodology, by proposing a system able to promptly detect worsening of the older user's health status and consider, as above, different stages for the aggravation. To date the project is still in its infancy, for this reason we do not have rich physiological data nor environmental and periodical information yet (e.g., coughing, blood oxygen percentage weight and so forth). In the present work we focus on the description of the main components of the system and the preliminary analysis performed over synthetic time series data to test the current state of our health monitoring system.

[1] Omniacare official website: https://www.omniaplace.it/en-us/Solutions/OmniaCare

1.1. Related Initiatives

In the last decades, a growing number of research projects and commercial products have dealt with the development of e-Health solutions to promote Active and Health Ageing. Several EU funded projects have worked on Information and Communication Technology (ICT) solutions to early detect risks in different aspects of older people's lives. For example, the main ambitions of the EU H2020 My-AHA project[2] are the early risk detection and intervention to support healthy aging both in the physical and cognitive domain. The project relies on the deployment of AAL sensors, wearable devices, and smartphones, and through big data analysis to engage users in improving their lifestyle. EU H2020 projects GrowMeUp[3] and Radio[4] provide integrated and services through robotic-based approaches to encourage older persons to stay active longer. PreventIT[5] and REACH[6] are focused on monitoring the users' physical activity through the deployment of wearable and/or ambient sensors. Additional European research projects on the coaching of older adults which feature common elements to ChAALenge are: NESTORE [9], The CAPTAIN System [10], COACH Council of Coaches [11], and HOLOBALANCE [12]. All of these projects focus their attention to specific sets of domains of the user's life and on providing coaching systems to assist them.

The project ChAALenge is intended to overcome the limitations of vertical solutions with a strong holistic approach by addressing several aspects of the user's lifestyle and by considering them from the user point of view and offering a framework that in full is able to automatically exchange information with integrated and intelligent third-party systems.

The rest of the paper is structured as follows. Section 2 gives details of the project and its goals. Section 3 introduces the middleware. Section 4 introduces the main ML techniques considered so far, gives insights about anomaly detection in multivariate time series, and briefly present mid-term results. The last Section draws conclusions and provides suggestions for future advancements in the topic.

2. The Project ChAALenge

Heart failure in older adults represents a real problem of health care that, other than the obvious troubles for the affected, is capable of absorbing an ever increasing volume of public/private financial resources and manpower. The project ChAALenge introduces a novel approach to face the issue, by leveraging the synergistic use of ICT and Machine Learning (ML). The goal is to prevent both onset and worsening of the disease by taking advantage of an Ambient Assisted Living (AAL) system, to monitor the patient's habits in their everyday life environments, to build a customized profile to be used to identify changes in their routines that may suggest an exacerbation of their health status. Yet maintaining timely responses in critical situations, the project focuses on the development of a middleware infrastructure to ease the communication between sensors and actuators for the collection of health information and a software with highly

[2]http://www.activeageing.unito.it/en/home
[3]https://cordis.europa.eu/project/rcn/194088/es
[4]http://radio-project.eu/
[5]http://www.preventit.eu/
[6]http://reach2020.eu/

customized predictive skills capable of foresee, and then avoid, the onset of acute issues. As the health status gets worse, the patient is encouraged to contact their own general practitioner or cardiologist based on the severity of the aggravation. For instance, by providing to the patient, their relatives, or directly to the attending physician reports from which infer the need of more frequent or specific controls, suggestion for a healthier lifestyle, or warnings indicating potential risk to health conditions.

2.1. ICT essential

The user's conditions in everyday situations and the support of specific services can deeply affect their quality of life, independently of the health status. Accordingly, it is important the enhancement of their everyday living environment (i.e., home) as primary place of care, for instance, through the support of information technology and AAL. Based on such assumptions, home care strategies perfectly fit the Mark Weiser's ambient intelligence vision [13]. To be effective and efficient, technologies should guarantee some requirements like: the integration in living environments (embedding); the exchange of information with each other (interoperability); the detection of both the user and the context in which he/she operates (context-aware); the adaptation to new scenarios and the user's needs, including changes (proactivity, adaptivity, and customization); the ability of hiding to the user the complexity they are made of, disappearing into living environments in a non-intrusive way (transparency). The effectiveness of the health status prediction depends on the knowledge of the patient, their current health status, habits, and changes. Since we are different from each other, individualization and customization become the basic components in the patient's dynamic profiling. Constant monitoring and virtual badge (i.e., profile customization) are the enabling requirements for the detection of worsening in the health status of the patient, preamble of the heart failure onset. This requires the use of efficient methods and techniques for collecting, transmitting, receiving and processing data. In the following we introduce the main sensor nodes made available by project partners, by reserving the description of the middleware to the next section.

2.2. Monitoring Parameters

To better select the most significant behaviors and habits to be monitored for heart failure onset detection, we held multiple working sessions with an expert cardiologist. Based on the technologies made available by the project partners, the physician suggested potential parameters to be monitored based on their own clinical experience rather than through classic clinical parameters made available by official prevention and treatment protocols. Table 1 gathers meaningful parameters to be monitored, their descriptions, the time duration, and the associated sensor technologies in use.

The patient health monitoring system comprehends the following cyclical steps:

- collection of information of both patient's health status and environment by means of a monitoring service software module;
- data processing and data analytic through an information management module;
- introduction of ML techniques and use of a decision-making application inferring the diagnosis based on data processing results;

Table 1
Environmental Monitoring for Detecting Health Status Worsening

Parameter	Variation over time	Duration (minimal)	Device(s) and Sensor(s)
`Weight`	Sudden increase of body weight	10 days	OMRON - VIVA weighing scale
`Cough`	Increase of night coughing	30 days	Audio robot UnivPM, microphones
`Stairs`	Time required to ascent and descent stairs	30 days	App WN Lab (CNR-ISTI), passive infrared sensor, proximity sensor, indoor positioning system
`Rest`	Daily rest time, especially after physical activity like ascending and descending stairs	30 days	Pressure sensor under the pillow/chair/sofa, proximity sensor, App WN Lab (CNR-ISTI), indoor positioning system
`Distance traveled`	Reduction over time of the distance traveled on foot, by bicycle, etc.	30 days	Cyclette eResult for Serious Game
`SpO2`	Reduction over time of peripheral oxygen saturation	10 days	Non-invasive pulse oximetry sensor technology by CNR-IMM
`Bathroom`	Increase in daily access to the bathroom	20 days	App WN Lab (CNR-ISTI), passive infrared sensor, indoor positioning system technology

- translation from decisions to commands and forwarding to output devices (i.e., home automation actuators capable of changing the current environment settings based on processed data and the patient's reactions).

The system functioning can be interpreted as a never-ending loop, whose steps are sequentially executed each time occurs an update in the state of a device belonging to the monitoring domotic environment.

2.3. Scouting for additional sensors

Table 1 introduces just a part of the sensors made available by all project partners, along with the list of significant parameters to be monitored for the detection of heart failure onset. Other sensors are expected to be employed during the progress of the project, based on the need to collect information on patient's vital parameters, and according to the application scenarios that will be taken into account. Currently, the additional equipment made available by project partners consists of various advanced tools, mainly for noninvasive monitoring of health status parameters. The sensory node Indoor Activity Analytic, for instance, is in charge of detecting

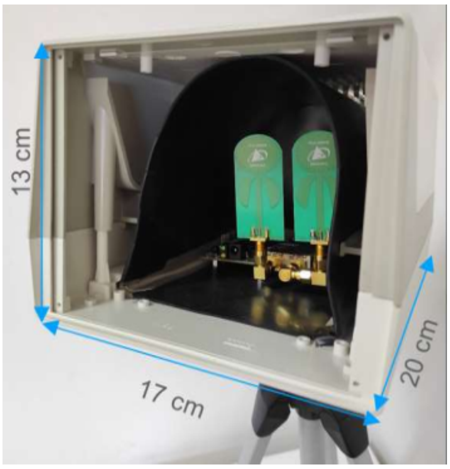

Figure 1: Enclosured RPS monitoring unit (Source: CNR-IMM).

falls and recognize the Activities of Daily Life by means of position and postural joints tracking. Another sensory unit available is the Radar Physiological Sensing (RPS). The node is composed by an ultra-wide-band Radar PulsON® P410 series with annexes software modules for signal processing and control, hosted on a real-time processing mini-PC unit. The enclosure of the monitoring unit is inside a shielded box, with a single opening and silicon coating to mitigate reflection effects that may affect the intensity of radar signals.

Figure 1 shows an image of the RPS monitoring unit. The information sensed by RPS are hearth and respiratory rate. The sensing operation is made in a noninvasive way by leveraging radar signal processing and ML techniques. The procedure comprehends wizard calibration, band-pass filtering, clutter noise attenuation, signal quantization and sampling, cardio-respiratory signal reconstruction through parametric optimization, signal extraction and heart rate estimation. Because of the very wide frequency spectrum in which operates, the module shows strong penetration ability of the impulse radio, resulting in detecting the position of the patients even in presence of obstacles (e.g., walls). Moreover, the use of very short radio pulses (i.e., *ps* order) allows to maintain a very low power spectral density (<40dBm/MHZ), restricting in this way jamming with other radio signals. Ultimately, the hybrid architectural nature of the module, capable of simultaneously operate as both radar sensor and radio transceiver, opens up the opportunity of applications in Body Area Network scenarios. Another couple of sensory nodes made available for the project are the Visual-based Vital Signs & Emotion Detector and the Wearable Vital Signs Monitoring & Fall Detection. Briefly, the Visual-based Vital Signs & Emotion Detector [14] is in charge of estimating vital parameters such as heart and respiratory rate, as well as oxygenation and facial expression of the monitored patient. The monitoring of the emotional status of the patient, additionally to vital parameters, gives further clues about the patient's psychophysiology status. The node comprehends Logitech C920 HD Pro webcams, which are very lightweight devices with 78° fixed diagonal field of view, auto-focus and automatic lighting correction. All such characteristics make the node versatile for the installation in a everyday life environment. The Wearable Vital Signs Monitoring & Fall

Figure 2: Smartex WWS for monitoring heart and respiratory rate.

Detection [15], instead, is responsible for fall event detection, posture monitoring, and other vital parameter for the assessment of health status and stress conditions. To the purpose, the sensory node may be composed of one of three little invasive and comfortable tools, that is: the Zephyr Bioharness3[7], the Smartex Wearable Wellness System (WWS) shirt/belt[8], and the ShimmerECG kit[9].

All the three tools, equipped with sensors and short- mid-range communication interfaces, are capable of collecting and wirelessly exchange information on heart rate, respiratory rate, and static/dynamic chest acceleration. The systems present similarities and differences with each other. For instance, both WWS and Bioharness3 share data through wireless interfaces but, while the former takes advantage of textile sensors to collect vital parameters, the latter leverages the plethysmography technique for sensing operations. Smartex WWS is present in the form of either T-shirts (all sizes) or a chest belt (adjustable). The sole difference is in the fit. Both models have two textile electrodes for detecting the heart rate and a piezoresistive sensor for detecting the respiratory rate. In the T-shirt case, the sensors are connected to a circuit board properly located in a slot inside the clothing. Figure 2 reports the circuit board and both the WWS T-shirt and the WWS belt. Briefly, the ShimmerECG kit integrates an accelerometer, a plethysmographic sensor (to be placed on the finger or earlobe), pre-gelled electrodes to detect heart/respiratory rates and a Bluetooth communication interface for data transmission. The manufacturing company provides both a chest belt (see Figure 3) and a wristband equipped with the above sensors to monitor the interested parameters. The synergistic use of all the previous tools enable to collect posture, fall event detection, respiratory and heart rate. Last but not least, among other (invasive) sensors made available by the project partners, it is worth

[7]https://www.zephyranywhere.com/system/components (accessed on 24 June 2022).
[8]https://www.smartex.it/wearable-wellness-system (accessed on 24 June 2022).
[9]https://shimmersensing.com/product/shimmer3-ecg-unit-2/ (accessed on 24 June 2022).

Figure 3: Shimmer cardio kit for monitoring heart and respiratory rate.

remembering the Glucose Skin Sensor that by means of an adhesive, waterproof, deformable and sensorized patch allows the indirect monitoring of blood glucose (by sweat sampling) [16]. As stated above, based on the need of additional vital parameter information, other sensors may be considered as the project evolves. It is worth to point out that the input core of the project is based on physiological data. Environmental information are temporarily considered subsidiary, as well as less invasive sporadic measurements like, e.g., the number of daily bathroom accesses or the resting time after climbing the stairs.

3. The Middleware

One of the main objectives of the project is to design a software architecture able to implement personal monitoring through indoor/outdoor sensors. The architecture must interface with intelligent devices, collect the data provided by sensors, transmit and store them for their use by analysis algorithms. The proposed architecture is based on the experience accumulated in previous projects, involving different scenarios such as: i) the development of a platform for monitoring older users' lifestyles to contrast sedentary, malnutrition, and cognitive decline [17]; ii) the implementation of a fully interoperable and context-aware domotic system [18]; iii) the design of a communication platform to integrate mobile and wearable devices with the existing pervasive environments [19, 20]; iv) the development of an unobtrusive monitoring system to evaluate of the user's sleep quality [21].

To monitor a person inside and outside their living environment is necessary to enrich the spaces they frequent and their body with intelligent devices capable of measuring quantities relating to their surroundings and their person. The software then transforms the measured quantities into signals comprehensible to information systems for their management and storage in appropriate databases. After having identified the use cases and chosen the hardware components (i.e. sensors and actuators), the software architecture must be designed and developed with the capability of:

- *Acquiring the quantities detected by intelligent devices:* The software must be able to interface with each intelligent device via special gateways capable of exploiting the

devices' outward communication mechanisms. The mode of interfacing depends mainly on two factors: the transmission medium and the communication protocol. Transmission medium can belong to two categories: wireless and wired. Typical examples of wireless transmission media are Bluetooth, NFC, Wi-Fi and InfraRed. Typical examples of wired protocols are Ethernet, USB and Thunderbolt. Transmission protocols, on the other hand, define how two or more entities communicate. The best known, standardised and open protocols are HTTP, TCP, UDP, SOAP and UPNP;
- *Carrying out possible data format conversions and/or normalisation:* The data from the sensors may not conform to the model used by the platform. For example, the data might be expressed in a different unit of measurement from the one used or need further processing, such as normalisation, for their use;
- *Storing environmental and patient data:* Every single value retrieved by sensors must be stored to not lose the information over time. Typically, data are stored in specific software structures capable of organising and quickly retrieving historical data (databases) using tools that interface information storage systems.

The interactions between the designed middleware platform and the main hardware and software actors are shown in Figure 4. The *sensing node* is a data emitting entity characterized by a set of properties that periodically produce information with a predefined format (e.g. temperature, motion and pressure sensors). The *actuator* is a service provider entity characterized by a set of properties on which an action can be invoked and from which a result can be received in response. The *application* is a software module able to both provide a service, to generate data and to actively search for sensors and actuators available on the platform.

Once the data has been collected, intelligent algorithms must retrieve and process them, combining environmental and patient body information to identify changes in the patient's state of health. For this purpose, it is necessary to design the middleware with the ability to also retrieve historical environmental and patient data, interfacing the algorithms with the information storage systems containing the measures.

In this scenario, at the centre of the architecture, a software component that works as middleware (Figure 5) must implement a network infrastructure to interconnect devices using different communication protocols with the health services. To this end, each communication standard is represented as a sub-network connected to the middleware core through modules that work as gateways (e.g. KNX Gateway, Bluetooth Gateway, ZigBee Gateway) between the wired and wireless device busses and the domain logic of the middleware core. The main task of the middleware is to route messages between gateways correctly. In this way, devices can send and receive commands and notifications from/to other devices belonging to sub-networks. In addition, the middleware uses a complete abstraction of heterogeneous technologies to represent devices, services, interactions and events. The abstraction layer acts as a common language for middleware components interoperability and is mainly composed of two sub-languages: one describes the characteristics of the devices, the available functions (services), the processes through which interactions with other devices must take place, and the models of standardised data types that provide a suitable intermediate representation to allow information marshalling between heterogeneous technologies; the other describes the messages exchanged throughout the framework. Messages that can be of two types: (i) command, when requesting the execution

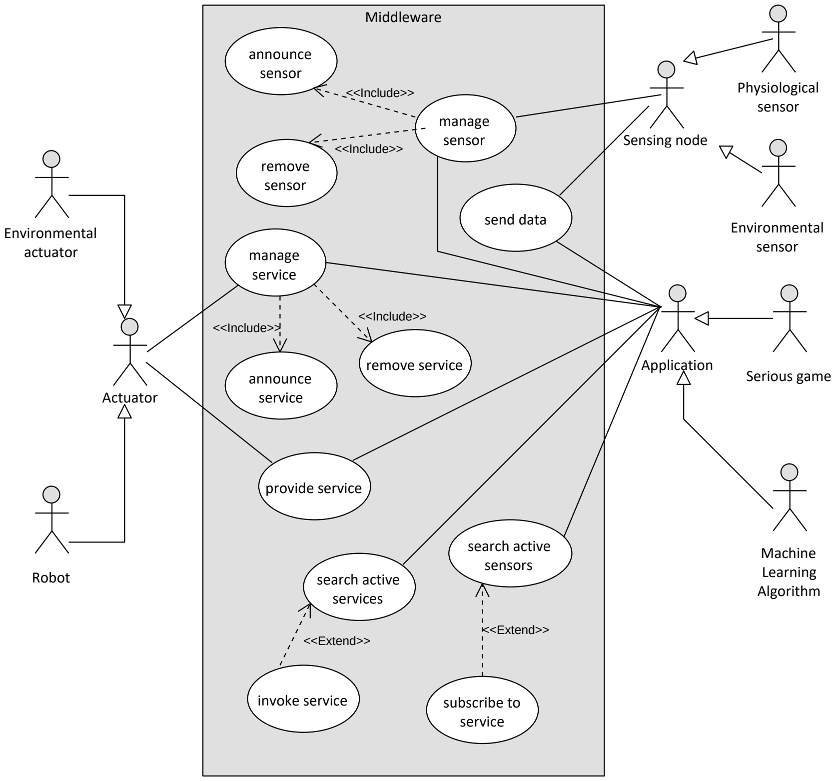

Figure 4: Interactions between the main actors and the middleware platform.

of a service belonging to a device; (ii) event, both when a change of state occurs in a device or when the device sends the periodic updates of detected values.

Once the values are received from the devices, the middleware stores them in a database and, if needed, it sends them immediately to the ML algorithm for their real-time processing. However, ML algorithms may also request historical patient data to the middleware that, in turn, queries the database to produce the required information to the requester. Moreover, the middleware provides a platform able to run on both desktop and mobile environments ensuring the privacy of the transmitted user data by operating secure connection channels.

4. Predicting Variations on Health Status

To make customized predictions about the health status of each patient, the data collected through sensors must be processed by an ML algorithm. To date, ML models considered for tests fall into the domain of unsupervised and semi-supervised learning. The rationale is that making predictions on health status of a patient is a domain with no (or with a very restricted number of) labeled data. Accordingly, we temporarily ruled out binary and multi-class techniques. The current focus is on unsupervised learning techniques, with a specific interest for multi-scale, attention-based autoencoders that leverage the synergistic use of convolution and recurrence.

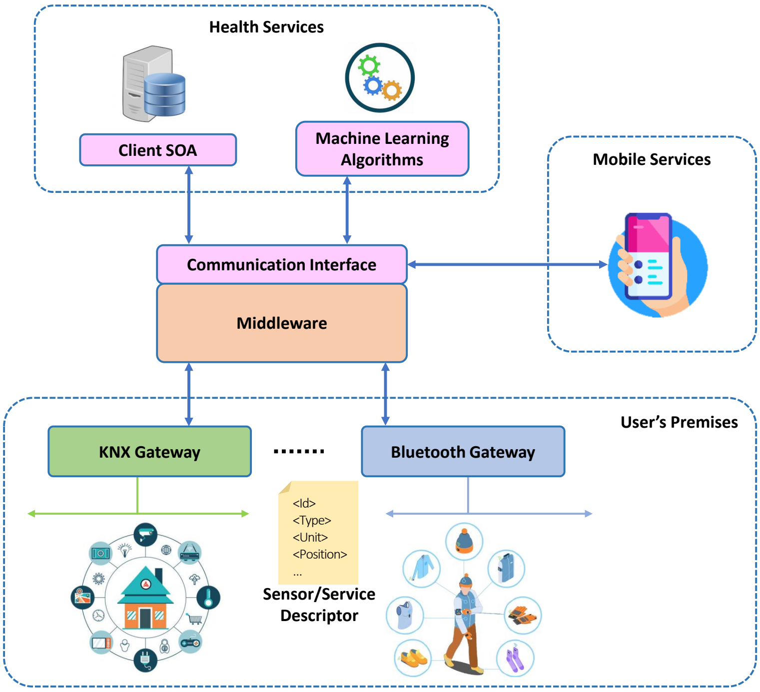

Figure 5: Software middleware architecture with sensors and health services.

The former is able capture spatial information of the feature maps produced by input data. The latter, in the form of attention-based Long Short-Term Memory (LSTM) cells, is able to apprehend temporal aspects of the data streams. Of our interest is the Multi-Scale Convolutional Recurrent Encoder Decoder (MSCRED) [22], an attention-based ConvLSTM neural network developed to capture both temporal and cross-channel anomalies in Multivariate Time Series (MVTS). The goal is to capture MVTS space-time features and detect temporal and cross-channel anomalies on the basis of reconstruction errors, or loss, obtained as difference between the original multi-scale signature matrices and the reconstructed ones. In this context the MSCRED is applied to provide a feasible solution for the detection of small changes in human habits and, in full, worsening in patients' health status to promptly detect situations of heart failure onset. Intuitively, the network captures spatio-temporal information from inter-correlations of time series. The data dimensionality is guaranteed by the use of different window sizes, packed three-by-three, that overlap to each other. The network performs well on harmonic series and data sets made up of chronologically ordered sensor information, e.g., belonging to a power plant. But there is no evidence of its proper functioning in the domain of health care for older adults. The implementation of the framework requires some steps. Firstly, the processing of health monitoring data to obtain correlation matrices from such weights to feed the network. Secondly, the encoding of spatio-temporal information and construction of feature maps through a convolutional encoder and an attention-based recurrent neural network with LSTM cells. Thirdly, the use of a convolutional decoder to reconstruct the correlation matrices and a square loss function to perform the end-to-end learning. Lastly, the computation of the anomaly score as residual matrix obtained as the difference between the original matrix and the reconstructed one. In case of missing data (due to, for instance, signal interference) we are considering two possible solutions for real time processing: either remove the entire temporal slot in which data are incomplete, or temporarily reduce the dataset dimensionality by dropping the faulty channel and reconsidering the thresholds (if any) accordingly. Differently, for offline statistical analysis we are considering to replace the missing values by applying techniques like median, interpolation, last/next observation carried forward/backward and so forth. We do not go into details of the MSCRED functioning, and we refer interested parties to [22].

4.1. Anomaly Detection in Multivariate Time Series

Briefly, the detection of anomalies in MVTS refers to the problem of identifying, within a data stream of several chronologically ordered channels, rare and distinct schemes (or isolated observations) that deviate from their normal trends. Such schemes are often labeled as *outliers*, to point out their irregular behavior [23, 24]. Fundamentally, there are two main kind of anomalies that can occur into a MVTS: **temporal anomaly**, which occurs within each single channel when it deviates from its regular behavior (e.g., the increase in body temperature due to a seasonal flu); **cross-channel anomaly**, which occurs as correlation between different channels that present irregularities on their joint historical behaviors. Of the two, the cross-channel anomaly is the more difficult to detect because of the common regular trend manifest by each channel individually taken. To date, many MVTS anomaly detection techniques have been investigated for different research areas. It is worth remembering that among the plethora of MVTS anomaly detection algorithms developed so far, the main method families span from classic ML techniques to Deep Learning [25, 26], from stochastic learning to statistical regression [27, 28], and so forth. The issue of detecting the worsening of the patient's health status to prevent the onset of heart failure can be faced as an anomaly detection problem. The change in health status may depend on a single factor or cross factors, and often this is due to imperceptible changes in lifestyle habits. That is why we need a predictive system able to detect both types of anomalies. In the next subsection we introduce some preliminary results obtained by applying an unsupervised learning approach to a synthetic data set.

4.2. Preliminary results

To test the functioning of the selected ML model over physiological data, waiting to obtain real environmental data as the project evolves, we run MSCRED on a synthetic dataset composed of time series reproducing sinusoidal signals typical of health monitoring sensors. Generally, synthetic time series data are used to both augment sparse data set information and test predictive algorithms in absence of real world information [29]. The model has been trained to learn data with no anomalies, while the test set has intentionally been enriched with perturbations in order to test the inability of the neural network to properly reconstruct the input signature matrix in their presence. Precisely, the data set is made up of one-hundred channels (i.e., sensors), each one with a different frequency, and several time-steps. Temporal patterns of the synthetic MVTS data are modeled as trigonometric functions, randomly selected for each signal. To generate the anomalies a little perturbation is added to the generated signals. The conditional expression, as

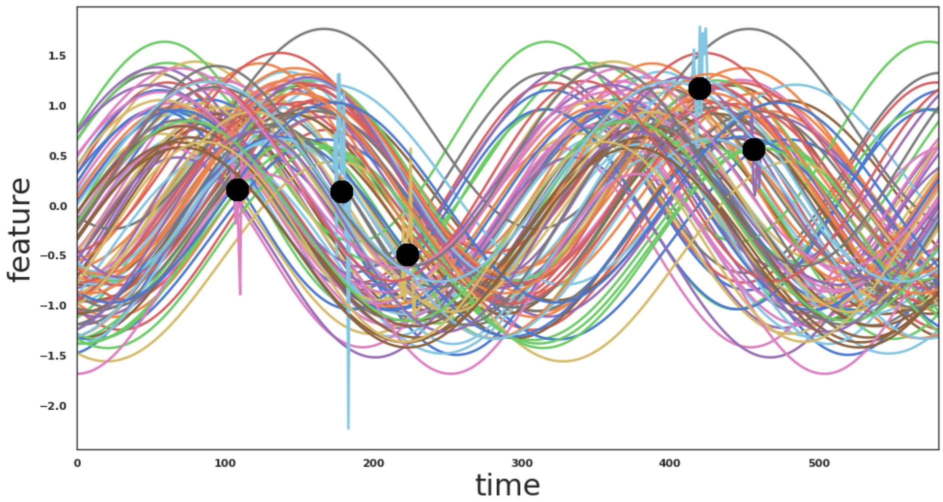

Figure 6: Sample fragment of the perturbed data set obtained by plotting synthetic health monitoring information. Anomalies have been highlighted with black spots.

introduced in [22], is as follows:

$$TS_i \begin{cases} sin[t - t_0/w] + \lambda \cdot \epsilon, & \text{if } k = 0 \\ cos[t - t_0/w] + \lambda \cdot \epsilon & \text{otherwise} \end{cases}$$

where TS_i stands for the i-th time series channel, k is a 0/1 token randomly selected, sin and cos $[t - t_0/w]$ are trigonometric functions applied to the ratio between time delay $t_0 \in [50, 100]$ and frequency $w \in [40, 50]$ to reproduce periodic cycles, and the dot product in tail is a scaled random Gaussian noise to simulate perturbation within the time series. Figure 6 shows a fragment of the test set with five perturbations (highlighted by black spots) as part of the synthetic health monitoring data. To train the model, also on the basis of better empirical results, we chose the following setting: gap time 1, window size [10, 30, 60], max step 5, batch size 32 and learning rate 0.0002.

The residual matrix computed over test set data identifies 37 broken elements, obtained as difference between the original correlation matrix and the reconstructed one. Such value highlights the network failure to correctly reconstruct the input matrix in presence of perturbations and defines the anomaly score. In Fig. 7 are shown the anomalies identified by MSCRED as broken elements of the residual matrix. The test corroborate the goodness of the candidate neural network in detecting anomalies (i.e., potential variation in the patient's health status) over synthetic health data. Ultimately, it is worth noting that such a technique, being based on the analysis of multidimensional time series information, can be applied to other domains than the current one. Because of these results, we expect the same (or quite similar) behavior of the algorithm over real data. The effort is to select the appropriate information capable of obtaining and clearly interpret the internal sectors of the residual matrix.

Figure 7: Broken elements of the reconstructed residual matrix as anomaly score.

5. Conclusions

In this work we have introduced a summary description of the elements and mid-term results of the project ChAALenge. In particular, we focused on sensor technology for collecting patient health data, the interfacing middleware between sensors and actuators, and potential artificial intelligence algorithms for health status prediction. Preliminary results based on a synthetic data set were also presented to test one of the most promising ML algorithm, i.e., MSCRED. Such results corroborated the functioning of the predictive model by identifying anomalies and, in full, potential aggravations in the patients' health status. Regardless the considered scenario, being it a house where a single patient lives, or being it a nursing home where multiple patients require cures, the algorithm should be able to provide *ad hoc* predictions. To do so, we are considering an implementation able to train multiple copies of it over each single patient's personal data. With respect to the economic sustainability of the equipment required to pursue the project goal, we are taking into account non-invasive solutions that enable the reuse of both allocated devices and sensors. Currently, the project ChAALenge is halfway and still work in progress. To properly evaluate the proposed solution, it is necessary to collect real-world data to make inference in field-test. Pursued this goal, we will be able to corroborate the real predictive skill of the model. Otherwise, there will be made architectural adjustments, also according to the empirical results achieved for improving the efficacy, the effectiveness, and the predictive capabilities of our system.

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