Physiological Data Measurement in Digital Manufacturing

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***Abstract*—As industry is moving towards a new digital revolution, identifying workers' mental and physical status is key to improved productivity in a digital manufacturing scenario. The main objective here is to provide an overview of sensing technologies in digital manufacturing and discuss suitability for taking physiological measurements of workers collaborating with robots. A method for rating physiological sensors in digital manufacturing application areas has been discussed which takes into account expert reviews. Selected commercially-available sensors are rated based on 9 evaluation keys (wearability, form-factor, mobility, pre-training, data-exchange capability, on-board filtering, ease-of-use, cost, and calibration) for digital manufacturing. The result is a scorecard of available sensors with feasibility to be used in digital manufacturing. In a given category, this data allows the selection of the best available sensors for certain use cases. The method to score the sensors has been explicitly explained to allow readers to expand on and contribute towards the data.**

***Index Terms*—Industry 4.0, physiological sensors, manufacturing, collaborative manufacturing**

I. Introduction

The manufacturing industry is currently experiencing a shift towards the use of more digital technologies. Improvement in data analysis techniques and artificial intelligence has allowed the development of digital manufacturing technologies to deliver increased productivity. Workers' well-being has been a topic of much recent consideration in digital manufacturing, especially in tasks where workers must interact with machines. It is already well established that certain physiological signals are good indicators of fatigue - both cognitive and physical [1]–[3]. Physiological sensing thus holds the key to further increasing productivity by monitoring fatigue in workers. A major hurdle however is the variety of players, both industry and research based, in the physiological sensing domain. There have been several studies explaining bio-signals and associated sensing technologies [4]. Yet, users continue to face problems in selecting the best sensor for their use case.

In this paper, we survey physiological sensing techniques and rate them for suitability in digital manufacturing. In order to determine the feasibility of physiological measurement techniques, a heuristic expert evaluation has been executed to assess commercially available physiological sensing based on the following criteria - ease of use, need for calibration, validated by third-party, accuracy, reliability, and data analytic tools. In the following section, related work followed by analysing the feasibility of using some notable commercially available sensors is discussed.

II. Related Work

A. Physiological sensing

Physiological signals are the data from the human body that convey the information about a person's state. There are eight main physiological measurements - Audiology, Cardiac Physiology, Gastrointestinal Physiology, Neurophysiology, Opthalmic and Vision Science, Respiratory Physiology (Including Sleep Physiology), Urodynamics, and Vascular Technology [5]. The main focus of this paper will be specific techniques in Cardiac Physiology, Neurophysiology, and Respiratory Physiology due to their relevance in determining mental and physical fatigue [1]–[3].

1) Heart-rate: One of the most commonly used physiological signal to determine workload and fatigue, heart-rate is the frequency at which the heart beats in a minute [6]. It is one of the earliest as well as the most understood physiological signal to be measured [7], [8]. Current technology makes it possible to measure heart rate with $\pm 2\%$ error during physical exercise [9]. Heart-rate can be determined by detecting either the heart-beat or the arterial pulse [8] through the use of bi-potential electrocardiogram (ECG) electrodes, piezoelectric sensors and strain gauge, chamber plethysmograph, photoplethysmograph (PPG), oscillometric blood pressure instrument, contact microphone, and electronic stethoscope. The most commonly used techniques are ECG and PPG. Using heart-rate for determining workload and fatigue has numerous advantages - well understood, easily found sensors, fast response to changing workload, and accurate. A major disadvantage is however that change in heart-rate is not always related to fatigue or workload.

2) Respiration: Respiration rate is measured as the number of breaths per minute and is directly responsible for the degree of oxygenation in the blood. It is crucial to measure the breathing rate for sleep study analysis, critical care, and anaesthetics. Studies have shown that breathing rate, along with other physiological signals such as oxygen saturation, assists in finding chronic heart failure and other cardiopulmonary conditions in patients [3]. Breathing rate can be measured in various ways such as using Accelerometry (ACC), and PPG [10], [11].

3) Thermography: Thermography is the process of measuring temperature and heat patterns in the body using a thermal or infrared camera. Skin temperature is non-uniform throughout the body as organs protruding farther from the body (e.g. nose) have lower skin temperature. Skin temperature can be a good indicator of stress as some studies have found that the temperature of the nose region drops when a person is stressed out [12].

4) Galvanic Skin Conductance: The conductance of the skin changes with the amount of sweat present on the skin. This affects the conductance of the skin, which can be measured using a Galvanic Skin Response (GSR) or Electrodermal Activity (EDA) sensor [13]. The skin conductance changes when the user is excited, frustrated, or stressed [13].

5) Pose: Pose, or body movement can be used to estimate fatigue and is also a reasonable indicator of physical disability [14]. People in fatigue exhibit various visual cues which can be easily identified using facial and body features [15]. Fatigue can be estimated by determining the decrease of the total amount of movement over time [14]. Using externally mounted cameras and ACC it is easy to obtain a good estimate of the pose, and other physical parameters of the human body [14].

B. Heuristic Analysis

Heuristic analysis is an easy and cost effective method to identify usability of hardware or software [16], [17]. This method determines usability by comparing systems against a list of predefined "heuristics," or rules that describe good usability [18], [19]. Traditional heuristics are suitable to evaluate most user interfaces [20], however, there is still a necessity to have physiological sensing domain specific heuristics to ensure specific issues related to this particular field are identified.

III. Method

A. Devices

The sensors selected for this study fulfill two major criteria. First, they are relevant in terms of determining workload and fatigue. Second, they can be used in a digital manufacturing scenario. Keeping these two criteria in mind, good workload estimation physiological sensing techniques such as brain activity, muscle activity, and pupillometry were excluded since they are not suitable for a manufacturing environment.

We have selected 3 pairs of devices/systems for evaluation across various physiological measurements. They are as follows:

1) FLIR A65SC: This thermal camera has a resolution of 640x512 pixels with a thermal sensitivity of less than 50 mK. It can measure temperature of a minimum spot the size of 100 microns and operates at a temperature range of -25°C to 125°C. It streams data to a PC through a Gigabit Ethernet connection.

2) DS18B20 Thermocouple: This is a high temperature water proof digital temperature sensor which operates between temperature range of -55°C to 125°C. The sensor is accurate to ± 0.5°C from the range of -10°C to 85°C and can be queried for data in less than 750ms. The signal from the sensor is digital in nature and can be read from a single pin using a micro-controller.

3) VICON: Vicon is one of the industry leaders in marker based motion capture systems. This system uses multiple cameras fixed in various positions to track markers within region of interest. Based on the number of cameras, the accuracy and occlusion can be improved. There are 6 different types of cameras available to set up a vicon tracking system. The cameras vary in specifications such as resolution, shutter speed, form factor, and function.

4) Picam and Openpose: The Raspberry Pi Camera Module V2 (Picam) is a small camera module for the Raspberry Pi computer system. It has an 8 megapixel Sony IMX219 sensor capable of taking 1080p30 videos. It supports third party libraries including Picamera Python library for development. Openpose is real-time multi-person system to detect human body, hand, facial, and foot keypoints [ref - openpose website]. It is capable of doing both 2D and 3D pose estimations and supports multiple operating systems and hardware platforms.

5) Zephyr: Zephyr is a wireless ECG heart rate monitor which monitors performance through the help of smartphone app. It uses Bluetooth for data transmission and works with Android, Windows, as well as iOS platforms.

6) Arduino Heart Rate Sensor: There are numerous PPG sensors available with plug and play support for Arduino micro-controllers. A few notable ones are MAX32664 pulse sensor, SEN0203 Heart Rate Sensor, and Maxim Integrated MAX30102 High-sensitivity pulse oximeter sensor. These sensors are fairly cheap and used for hobby kit purposes. They are marked to be not used for any form of medical diagnosis.

B. Heuristic Evaluation

For heuristic evaluation of the sensors, one of the expert evaluates and rates the selected sensors - predominantly one which they have the most expertise in. It is to be noted that all the experts consulted for this study had expertise in more than one physiological sensing technique. The evaluation and rating done by the expert for a particular sensor is then reviewed by the other experts. The rating is a reflection of how well the sensor satisfies the metric on a 5 point scale of 0 to 1.

The evaluation metrics for this study are adapted from Wilcox and Feiner's work on evaluation of physical activity monitors [19], [21]. Since the sensors are being considered for evaluation keeping a digital manufacturing scenario, we bring in metrics such as wearability and mobility of user as additional sub analyses under the "Usability" heuristic apart from existing sub categories like form factor and ease of use. For "Ease of Integration" heuristic, we introduce cost, calibration, on-board filtering, and pre-training as essential sub categories apart from existing data exchange capability.

1) Wearability: This metric rates the comfort of wearing the sensor for longer periods. If the sensor cannot be worn comfortably for long periods, it will get a lower score. If the sensor is comfortable to wear and does not affect the user in the long run, it will get a higher score in this metric.

2) Form Factor: This particular metric is used to rate how portable the sensor in consideration is. It can be a stationary device on one end of the spectrum (such as an MRI machine) and completely portable on the other (such as a smartwatch).

3) Mobility of user: This metric category rates the mobility of the user for a particular sensor. Sensors which are tethered to a base station or other such systems restrict user mobility to a limited space. The same is also true for cameras with limited focal length. Sensors such as PPG based smartwatches do not limit user mobility at all.

4) Ease of use: Ease of use is a subjective measure according to the user. It describes the ease of the overall process of using the sensor to obtain data. This involves the process of setting up the sensor before use, calibration, recording data, processing it, and making sense of it.

5) Cost: It is one of the most important factors to consider while deciding to use a sensor for a particular use. This key has been further subdivided into ranges spanning across various orders of magnitude in terms of the sensor's cost.

6) Calibration: Sensors require to be calibrated to be appropriately used and obtain correct data. Some sensors can be used without being calibrated for quite some time while other sensors may require calibration every time they are used. The best-case scenario for a sensor would be no-calibration needed, whereas the worst-case scenario would be requiring calibration before every use.

7) On-board Filtering: It is necessary to filter the signal obtained from sensors. Filtering can be incorporated in various ways, such as using hardware or software-based filter. The on-board functionality key spans from having no filtering to one where the data obtained is labelled for use.

8) Pre-training: From a researcher's perspective, pre-training refers to the process of acquiring the knowledge and skills required to use the sensor and acquire data. This can range from needing an expert to set up the sensor to a sensor that is intuitive to use.

9) Data Exchange Capability: The score from this criteria determines how easy it is to integrate a particular sensor into an existing system. The sensor may be completely non-integrable where one needs to process and make sense of data from it before feeding into the existing system to one that plugs and plays and produces data for direct use.

IV. Results

As mentioned previously, commercially available sensors with extensive use in research and industry were evaluated and scored by experts based on proposed heuristics. Depending on these scores, sensors from the same physiological measurement category are compared in the following section using radar charts. These charts assist us in visualizing the competency of the sensors based on the given heuristics. Coupled with the sensor data sheets, these charts prove to be an excellent tool to select sensors based on use case.

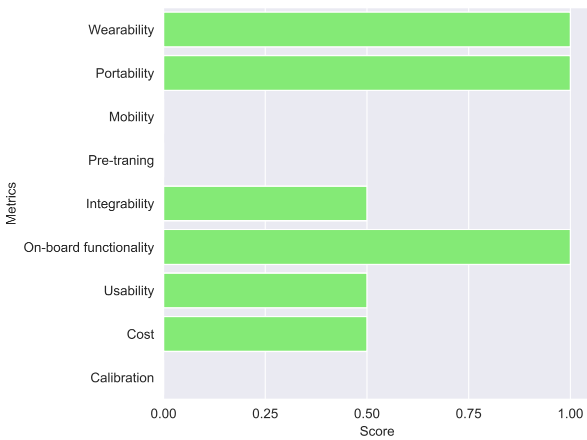
The comparison between Vicon systems and Picam based openpose systems (Fig 1) for pose tracking shows basically the same profile apart from differences in on-board functionality and cost. The results show that there is at least an order of magnitude difference in cost between both the pose tracking systems. Both the systems can be moved around and set up in a desired location without much issues. The systems don't have any issue with wearability as subjects are able to wear the markers (in case of VICON) and operate for long periods. In-depth knowledge of the systems and complex setup tasks are required to get the systems up and running which gives them a low score in pre-training. The pose data out from both the systems may need cleanups depending on the situation. Both the systems need to be calibrated every time before use assuming that they are removed from the setup position. One thing to take note of is that the accuracy of the systems hasn't been compared here as pose tracking accuracy for upto a few centimetres is not a matter of concern given the size and area of the systems involved.

It is less complex in case of thermal sensors to compare the Flir thermal camera and the generic thermocouple sensor to understand which would be easier to use (Fig 2). One thing to keep in mind, however, for this comparison would be that objectively, the Flir thermal camera would have much more accuracy and temperature range compared to the generic thermocouple. If the specific location is known where temperature measurement needs to be done, nothing beats the thermocouple sensor. However, if temperature is to be measured across a wide region with almost no restriction to mobility, Flir is a more fitting option.

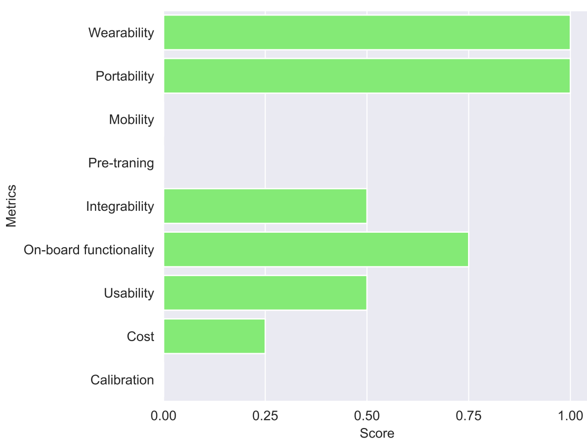
The comparison between a PPG based heart-rate sensor and the Zephyr ECG based heart-rate sensor is shown in Fig 3. Results show that as a standalone sensor, the PPG based heart-rate sensor is cheaper and provides similar usability experience as the costlier Zephyr. Nevertheless, if the data needs to be accurate and easily integrated into existing systems, the Zephyr ECG based heart rate sensor is the better choice despite the increased cost. Integrability and on-board functionality makes a major difference here due to the need to process data coming out of the PPG based sensor while the one out of Zephyr is readily usable.

TABLE I: Sensors and Scores

Sensors	Scores								
	Wearability	Portability	Mobility	Pre-training	Integrability	On-board functionality	Usability	Cost	Calibration
FLIR A65SC	0	0	0.75	0.25	0.75	0.75	0.5	0.25	0
DS18B20 Thermocouple	0.25	0.25	0.5	1	0.75	0.25	0.75	0.75	1
VICON	1	1	0	0	0.5	0.75	0.5	0.25	0
Picam and Openpose	1	1	0	0	0.5	1	0.5	0.5	0
Arduino based generic heart rate sensor	1	1	0.75	0.5	0.25	0.25	0.75	0.75	1
Zephyr	0.5	0.5	0.75	0.5	0.75	0.5	0.75	0.5	1

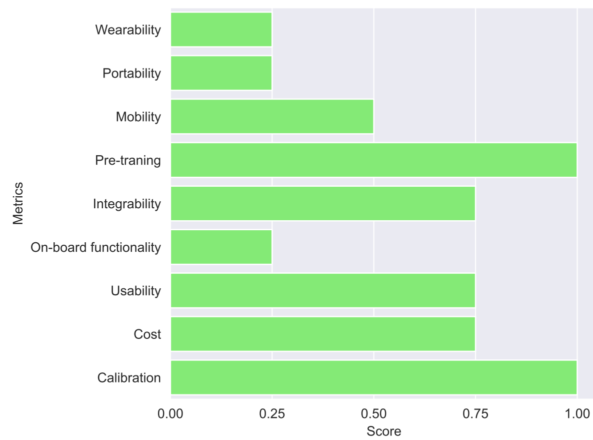


(a) Picam and Openpose

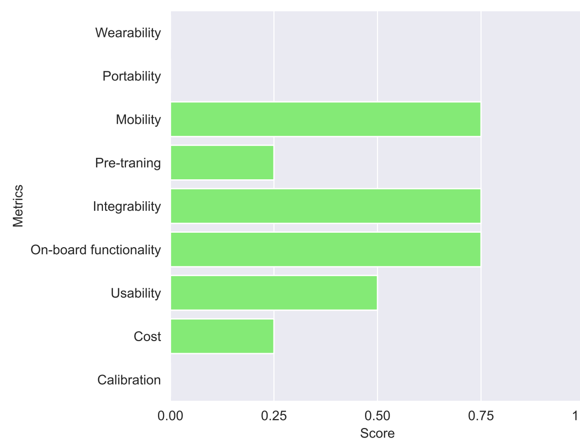


(b) Vicon

Fig. 1: Comparison of Pose Tracking sensors and systems



(a) Thermocouple sensor



(b) Flir Thermal Camera

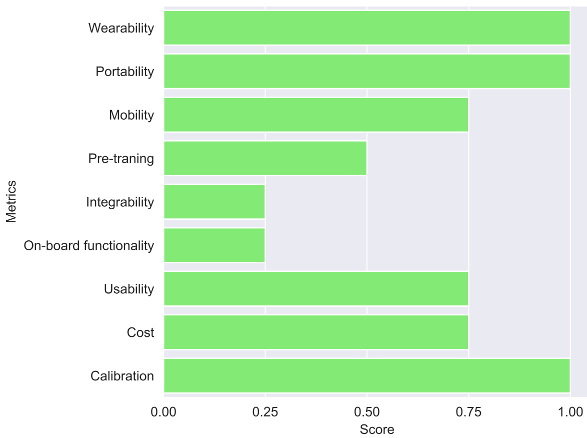
Fig. 2: Comparison of Thermal sensors

V. General Discussion

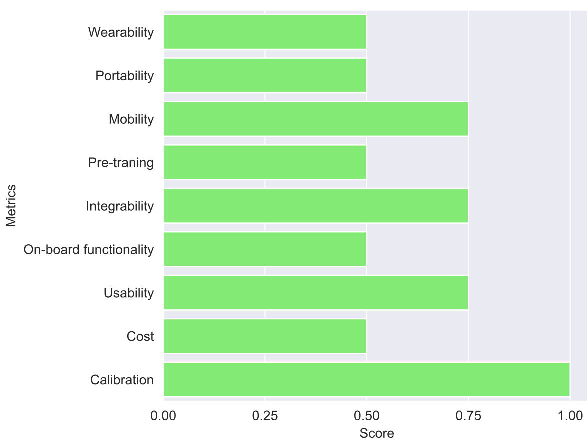
Our heuristic evaluation provides insight into sensors suitable for workload and fatigue estimation in a digital manufacturing scenario. The sensors and systems evaluated have numerous benefits that can be taken advantage of based on the situation. For work involving fairly direct correlation between heart rate and workload, PPG based heart rate sensor seems to be the best option. The main reason for this is relatively low cost while similar results compared to other costlier sensors. Manufacturing environment doesn't demand a very high accuracy in terms of the physiological data. This makes considering less expensive sensors a viable option.

For more complex scenarios where a direct correlation cannot be established between a particular physiological signal and workload, sensor fusion is the way forward. In such scenarios, consulting information from our and other such heuristic evaluations is a good starting point.

This work was a heuristic expert evaluation and thus there was no test done in an actual digital manufacturing environment. A major criteria for the successful integration of these sensors into a manufacturing environment is positive feedback from managers and floor workers. Also, the sensors were not explicitly tested for their accuracy or performance in a digital manufacturing environment. Those sensors which are



(a) PPG based heartrate sensor



(b) Zephyr

Fig. 3: Comparison of Heartrate sensors

known to be prone to noise have been excluded altogether for this expert evaluation. However, the evaluated sensors need additional work for further validation and readiness to be integrated directly into industry.

VI. Conclusion

Sensors have developed significantly over the last couple of decades leading to faster, cheaper, and more efficient ways for physiological measurement. With increasing use of data and artificial intelligence, sensors play an important role in bridging the gap between the physical and the digital world. Determining workload and fatigue in workers is the first step towards collaborative digital manufacturing. The next step involves using these signals to predict changes to workload on workers and adjust production line accordingly. This would lead to better productivity and higher overall job satisfaction.

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