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A sensor-centric survey on the development of smartphone measurement and sensing systems

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Abstract

Modern mobile phones, featuring high performance microprocessors, rich set of sensors and internet connectivity are largely diffused all over the world and are ideal devices for the development of low-cost sensing systems, in particular for low-income developing countries and rural areas that lack the access to diagnostic laboratories and expensive instrumentation.

In the design of a smartphone based sensing system different elements must be taken in consideration such as sensors performance, acquisition rate and privacy preserving strategies when personal data must be shared in the cloud.

In this paper a sensor-centric survey on smartphone based sensing systems is presented, covering different fields of application. Two different development approaches will be discussed: 1) the exploitation of the large number of sensors embedded in modern smartphones (high-resolution camera, microphone, accelerometer, gyroscope, magnetometer, GPS); 2) the interfacing with external sensors that communicate with the smartphone by the embedded wireless or wired communication technology.

Keywords: smartphone, measurement, sensors, embedded system, wireless communication, pervasive computing.

1. Introduction

Modern smartphones embedding multitasking operating systems (OS), high performance microprocessors, rich set of sensors as well as wireless and wired communication technology are very popular and largely diffused all over the world.

The first prototype of mobile device merging telephony and computing dates back to 1970s [1]. However, it was only in the early 1990s that, thanks to the introduction of the GSM based technology (2G) and the shift of mobile telephony communication from analog to digital, the first commercial smartphones reached the market. Moreover, the introduction of rechargeable lithium ion-cell batteries in 1990s helped to reduce the weight and price of mobile phones. The first commercial smartphone is Nokia 1011 that was released in 1992 and featured a microphone as embedded sensor. Since then, ever more powerful devices have been produced with increasing computing power, larger mass storage memory, higher resolution screen, larger set of embedded sensors and faster communication. A milestone in the smartphone development is represented by the commercial release of the first iPhone (iPhone 2G) by Apple in 2007: the device featured 2 MegaPixel integrated camera, a proximity sensor, an ambient light sensor and an accelerometer.

Different OSs have been released for smartphones. In the years 2000 – 2007 the market was dominated by Symbian, used the first time with the mobile phone Ericsson R380 in 2000, Blackberry, released by Research In Motion (RIM) in 2002, and Windows Mobile CE. In 2007 Apple introduced the iOS operating system for its iPhone and in the same year Google released the Android OS. Nowadays Android is the most popular smartphone OS with a market share higher than 80%, followed by iOS (between 15 and 20%), while Microsoft Windows 10 Mobile has a market share lower than 1%.

Smartphones are integrated with a rich set of sensors. Most devices feature a built-in high resolution camera, 3-axis accelerometer, magnetometer, gyroscope, GPS, proximity sensor, microphone, light sensor and temperature sensor. However, high-end devices also integrate other non-standard sensors: for example Samsung Galaxy S4 has a built-in sensor for temperature and humidity environmental monitoring; Google Nexus 5 integrates a pedometer for accurate step counting;

Samsung Galaxy 5S features a heart rate measurement sensor; Apple iPhone 8 Plus integrates a barometer; Sharp Pantone 5 integrates a sensor to detect harmful radiations.

Almost all smartphone sensors were integrated to support some functions of the device. For example the 3-axis accelerometer is normally used to provide information about the device orientation and to automatically switch between landscape and portrait screen orientation; the magnetometer exploits its feature of detecting magnetic field in compass applications to detect the planet's north pole; the temperature sensor monitors the device battery temperature to prevent overheating; the light sensor exploits its capability to measure the environmental light intensity to automatically adjust the display brightness; the proximity sensor can detect when the device is placed near to the user ear thus disabling some functions during the phone call. Nevertheless, a set of libraries, protocols and programming tools has been released to the public (Application Programming Interface, i.e. API) to allow the programmer to take control of the many sensors integrated in the mobile phone.

Modern smartphones also integrate modules for wired and wireless communication. In the case of wired data communication, Android devices rely on USB data transfer protocol while iPhone featured a non-standard 30 pin connector (replaced by the 8 pin Lightning connector since 2012). In the case of wireless communication, Wi-Fi is used for long range communication while Bluetooth covers the short range (few tens of meters) communication applications. Near Field Communication (NFC) is a RFID based wireless communication system that allows very short range (10 cm) power and data transfer that is also ever more integrated in modern smartphones. The integration of wired and wireless communication protocols allows the interaction between smartphones and external hardware to design innovative sensing systems that merge the versatility of ad-hoc designed electronic boards with the pervasive computing, large mass storage memory and internet access of modern mobile phones.

Sensors and sensing systems allow accurate and rapid measurements that can be easily implemented in automatic form. Sensor systems are used in a wide range of applications, from environmental

monitoring [2][3][4] to food quality assurance [5][6][7], from clinical analysis [8][9][10] to industrial applications [11][12][13]. Such systems are usually designed using microprocessor or microcontroller based systems where sensors output is acquired, converted to digital value by means of an Analog-to-Digital converter (ADC) and analyzed by the system processing unit. In this context, the use of smartphones as sensing system results in large cost reduction since the high-performance processing unit, display, user input, wireless communication modules as well as many sensors are already integrated in the device.

Smartphones diffusion is always increasing all over the world. The US smartphone users increased from 60.2 millions in 2010 to 106.7 millions in 2012 [14]. In 2014 Kakihara presented a survey showing how smartphone diffusion is increasing not only in developed countries but also in many developing countries [15]. Low-cost sensing systems based on smartphones have been proposed in different fields of application, such as for example in healthcare [16][17][18][19], point-of-care diagnostic [20][21][22], food analysis [23], agriculture [24], biosensors for portable biochemical detection [25][26], portable spectrophotometers [27], mobile microscopy [28], activity recognition [29] and intelligent transportation systems [30][31][32]. The availability of high processing power and wireless communication has also opened the road for crowdsensing applications, where the participants collect and share the measured data using their smartphones and send these data to central servers for processing [33][34][35]. A summary of review articles covering smartphone sensing for different fields of application is presented in Table 1.

In this paper, a survey of sensor systems exploiting smartphone will be presented. In sections 2, 3 and 4 sensing systems using the mobile phone built-in sensors (camera, microphone, accelerometer, magnetometer, gyroscope and GPS) are discussed. In section 5 sensing systems based on external sensors interfaced with ad-hoc designed hardware are presented. In section 6 prospects and challenges of smartphone based sensing systems are discussed. Finally, conclusions are drawn in section 7.

2. High-resolution camera

The high-resolution camera embedded in modern mobile phones can be used in a wide range of applications, from simple colorimetric tests to more advanced computer vision applications.

One application that has been deeply investigated is the possibility to use the smartphone to automatically read a test strip. Colorimetric test strips are used in a wide range of applications (measure of pH, detection of pathogens in urine, determination of the glucose level in blood) due to their low-cost and easiness of use: the sample under test is poured on the strip and the parameter of interest is estimated from its color change. Smartphone camera is then used to take a picture of the strip and analyze the color change. The main weakness of such application is due to the interference of the environmental light and non uniform characteristics of the camera among different phone models. To overcome such problems, many authors have placed the smartphone inside an ad-hoc designed chamber featuring its own illumination system, thus filtering out the environmental light interference, and implemented software calibration algorithms to compensate for the different camera characteristics. For example, Kim et al. in 2017 proposed a smartphone based system to read pH test strips [36]: the phone was placed inside a 3D structure with LED lighting system and calibration was carried out using paper printed reference colors. The system was tested with different solutions of known pH and an average error lower than 0.25 was achieved. A similar approach was used by Lee et al. for the quantification of 25-hydroxyvitamin D concentration using a gold nanoparticle-based immunoassay [37]: the concentration was estimated from the brightness difference between a detect and a reference area once the acquired image was converted to HSB color model, resulting in an accuracy of 15 nM, precision of 10 nM and a time response of 6 hours. Jung et al. proposed a system to measure the alcohol concentration in saliva in the range 0 – 0.3 % [38]. Yetisen et al. proposed an algorithm to compensate for the differences among different phone cameras and tested it with a 3-patch urine test strip (for the determination of pH, protein and glucose) [39]: the calibration was carried out by capturing and processing a set of reference images of known concentrations under a given light condition. However, changes in the environmental

light results in the need to re-calibrate the system. Shen et al. in 2012 developed a calibration procedure to compensate for different light conditions [40]. In 2017 Kim et al. proposed a smartphone based sensor to measure the blood hematocrit from 10% to 65% with a level of detection (LOD) of 0.1% [41]: in this case a microfluidic device, placed inside an acrylic box and illuminated with white light, was used and the hematocrit concentration was estimated from the red, green and blue components of the microchannel image captured by camera. Liu et al. in 2017 proposed a smartphone optosensor to measure streptomycin (STR) concentration in different food products [42]: the liquid sample under test is mixed with a colorimetric indicator (aptamer-conjugated Au nanoparticles) and placed in a cuvette; the light source is generated by three colored LEDs with peak wavelengths 473, 520 and 625 nm and transmitted through the sample; the transmitted light is acquired by the smartphone camera and STR concentration estimated from the measured absorbance ratio at 625 and 520 nm ($R^2 = 0.996$); the system was successfully tested with honey, milk and tap water. A low-cost colorimetric test suitable to detect the concentration of different types of biological macromolecules was presented by Dutta et al. in 2017 [43]: the sample under test, placed in a cuvette with a suitable reagent to produce a change in color, is irradiated with a white LED and a picture is taken with the phone camera. Image pixels are converted to HSV color space and the average brightness (V) of the image was found the parameter best suited to estimate the analyte concentration. Three different biomolecules were tested (BSA protein, catalase enzyme and carbohydrate) and a very good correlation with the results of a commercial spectrophotometer was found.

In 2016 Bueno et al. proposed a smartphone fluorescence analyzer to detect ochratoxin A (OTA) concentration in beer samples [44]: the sample, placed in a plastic cuvette is irradiated with a UV LED (wavelength range 360 – 380 nm); the presence of OTA produces a fluorescent radiation at 460 nm that is detected by the phone camera by analyzing the RGB components of the acquired image to extract the blue component; the sensor features a linear response in the OTA concentration range 2 – 20 $\mu\text{g/L}$ with a LOD of 2 $\mu\text{g/L}$. Fluorescence analysis with smartphone has been also

investigated by Hossain et al. in 2017 for the quality evaluation of olive oil [45]: the oil sample is irradiated with a UV LED (peak wavelength 370 nm), the reflected radiation collected by an optical fiber and the fluorescence spectrum measured with the phone camera. Tests have been carried out under different light and health conditions and the results have shown that the system can detect the oil degradation level. Hakonen and Beves in 2018 designed a smartphone system to discriminate extra virgin olive oil from lower grade edible oils [46]: the olive oil sample, placed in a vial, is irradiated with a 405 nm UV LED and the fluorescence is detected at 90° angle by the phone camera. The acquired image was converted to the HSV color space and hue histograms calculated to discriminate the different types of oil. McCracken et al. in 2017 developed a smartphone system to detect bisphenol A (BPA) concentration in water samples [47]: the water sample, added with 8-hydroxypyrene-1,3,6-trisulfonic acid, is placed in a cuvette and irradiated with a 460 nm LED. The fluorescence radiation at 512 nm is measured with the phone camera by analyzing the acquired picture in RGB color space. The results have shown that the system is capable to detect BPA with a detection limit of 4.4 μM and a maximum concentration of 200 μM. Different smartphone models were tested and the results suggested that the 460 nm LED can be replaced with the phone flash LED with comparable accuracy.

Color analysis of images taken with the smartphone camera was also used to estimate the cloud coverage [48] and to detect the surface corrosion of iron [49][50][51]. An electrochemiluminescence (ECL) smartphone system was proposed by Delaney et al. in 2013 [52]: a paper fluidic element, in contact with a screen printed electrode, is loaded with the luminophore $\text{Ru}(\text{bpy})_3^{2+}$; with the phone audio channels a square wave voltage waveform (V_{peak} 1.77 V, frequency 7.143 Hz, duty cycle 71.43%) is applied to the electrodes; in presence of the target compound, light is generated by the luminophore, and detected with the camera by analyzing the image red component; the system was tested with two different target compounds, 2-(dibutylamino)ethanol and L-proline. Park et al. proposed a smartphone system based on Mie scattering that measures the concentration of *Escherichia coli* in water samples by using the phone

camera to detect the scattered light intensity from paper microfluidic sensor at different angles [53]: the system, featuring a response time of 90 seconds, is characterized by a LOD of 10 CFU/ml and in good agreement with the results from the reference technique. The same research group used the same principle to measure the bacterial concentration in meat samples [54].

Smartphone camera has been also used to make measurements of UV solar irradiation. This is a very important topic since prolonged exposure to UV radiations increases the risk of skin cancer [55][56]. On the other hand, UVA (320 – 400 nm) and UVB (280 – 320 nm) radiations affect differently human skin [57] and UVB exposure plays also a role in vitamin D synthesis [58][59]. Thus, measurement of both UVA and UVB solar radiations is important for human health protection. Smartphone embedded camera features a set of blocking filters to remove non-visible light wavelengths. Moreover, the coating of lens camera absorbs most of the UV light. Nevertheless, Igoe et al. in 2013 have shown how, by mounting bandpass filters in front of the phone camera to remove the visible light, UVA wavelengths can be detected [60]. This has been first validated by means of laboratory tests using an irradiation monochromator [60], then with in-the-field solar radiation [61] and an app was also designed to measure UVA aerosol optical depth and direct solar irradiance at the wavelengths 340 nm and 380 nm [62]. The same research group has also shown the feasibility of UVB wavelengths measurement using smartphone [63]. The phone camera was equipped with a 305 nm bandpass filter and the red component was found the parameter providing the highest signal-to-noise ratio. A good correlation ($R^2 = 0.98$) was found with a Microtops II sunphotometer using a quadratic model for calibration [64]. UVB measurement with smartphone camera was also used evaluate the atmospheric total ozone column [65]. UV radiation measurements using the smartphone camera were also reported by Wilkes et al. to detect the SO₂ emission from volcanic craters [66][67]: in this case, however, the camera blocking filters were removed and the lens replaced with UV transmissive anti-reflection coated plano-convex quartz lens of 6 mm diameter and 9 mm focal length [68]. Two bandpass filters centered on 310 nm

and 330 nm were mounted in front of the camera providing good correlation ($R^2 = 0.92$) if compared with a scientific grade UV camera.

Smartphone camera can also be exploited to design a low-cost and portable spectrophotometer [27]. A spectrophotometer is an instrument capable to measure the optical absorbance of the sample under test as function of the incident radiation wavelength. Different commercial instruments exist working in different wavelength regions (visible, near and mid infra-red, etc.). The spectrum measured by the instrument can be useful to detect various types of analytes, in particular when used in conjunction with multivariate statistical analysis such as Principal Component Analysis (PCA) and Partial Least Square (PLS) regression. Smartphone spectrophotometers exploiting the phone camera are limited to the visible wavelength range (400 to 700 nm) since the phone camera embeds filters to block non-visible light. A visible spectrophotometer based on smartphone was proposed by Dutta et al. in 2015 [69]. The working principle of the instrument is shown in Fig. 1 (a): a broadband light source is allowed to pass through a 50 μm pinhole and then through a collimating lens; the collimated light is transmitted through the sample under test, placed in a cuvette, and the emerging light is focused by a cylindrical lens to a transmission grating attached to the phone camera. A picture of the developed instrument is shown in Fig. 1 (b). The grating translates the wavelength information present in the radiation in its constituent colors that are detected by the camera (Fig. 1 (c)). The pixel-to-wavelength calibration can be achieved by testing the system with laser sources of known wavelength. The system, featuring a spectral resolution of 0.305 nm/pixel, has been tested to measure pH for river quality water assessment [69] and to measure the concentration of BSA protein and trypsin enzyme [70]. The same research group developed also a smartphone based evanescent wave coupled spectrophotometer that improves the previous version in compactness and portability [71][72]. Other smartphone based spectrophotometers have been proposed by Gupta et al. to measure the optical spectrum of color dyes and milk samples [73], by Souza de Oliveira et al. to determine Fe^{2+} in medicine samples and Na^+ in saline solutions and natural water samples [74], by Long et al. to design a portable Enzyme

Linked Immunosorbent Assay (ELISA) that can be used for clinical assays with a LOD that is identical or better than a standard ELISA microplate reader [75]. Gallegos et al. in 2013 proposed a smartphone based spectrophotometer where the sample under test is a label-free photonic crystal biosensor [76]: a photonic crystal was immobilized with protein A for the detection of porcine immunoglobulin G (IgG); when irradiated with a white light source, the photonic crystal features a resonant reflection at a wavelength of 565 nm that shifts to higher wavelengths due to the binding of the target analyte; IgG concentrations from 4.25 nM to 3.4 μ M were tested and a LOD of 4.25 nM was achieved. Yu et al. in 2014 proposed a smartphone based fluorescence spectrophotometer [77].

The pervasive computing of modern smartphones allows the development of portable computer vision sensing applications. One example is represented by automatic colony counter applications. Standard Plate Count (SPC) is the reference technique to measure bacterial concentration [78]: serial dilutions of the sample under test are prepared and inoculated inside Petri dishes (cylindrical plastic containers filled with agarized culture medium for bacterial growth); after an incubation time at the target temperature (usually 24 – 72 hours at 37 °C), the number of cell colonies grown on the dish are counted and this value is used to estimate the initial bacterial concentration. The counting process is time consuming and labor intensive. Since many microbiology laboratories must process hundreds of plates every day and every plate can contain hundreds of cells to count, manual counting can lead to eye fatigue and error. Smartphone based automatic colony counters exploit the phone camera to acquire a picture of the Petri dish, then apply a set of vision algorithms for boundary removal, image smoothing, image binarization and colonies detection to count the number of colonies. In the process of accurate colony count a critical point is the separation of partially overlapping colonies. Different smartphone based automatic colony counters have been presented in literature, such as the ones discussed by Zhang and Chen [79], Minoi et al. [80], Austerjost et al. [81], Poladia et al. [82] and Kumar et al. [83]. Other computer vision applications for smartphone include a system for continuous surveillance of fruit flies [84], a food recognition tool assisted by

image retrieval [85] and nutritional value estimation [86], a heart rate measurement system exploiting the time variation of acquired images of the user fingertip placed on the phone camera [87].

Portable microscopy based on smartphone has been also proposed in the field of point-of-care analysis and telemedicine, particularly in the case of developing countries and rural areas that lack healthcare facilities. Breslauer et al. in 2009 presented a smartphone based microscope that can work in brightfield and fluorescent imaging [88]. The schematic of the proposed system is presented in Fig. 2 (a): the eyepiece (20X) and the objective (0.85 NA 60X) are standard low-cost microscope parts; the filters are present only in the case of fluorescent imaging; the light source is an high power blue LED in fluorescent imaging, while it can be omitted or replaced with a white LED (in the case of scarce illumination) in brightfield imaging. A picture of the system is presented in Fig. 2 (b). Fig. 2 (c) and (d) show images of 6 μm fluorescent beads in the case of brightfield and fluorescent imaging, respectively. The system has been successfully tested with *P. falciparum* malaria-infected blood cells in brightfield imaging and with *M. tuberculosis* infected sputum samples in fluorescent imaging. A lens-free smartphone based microscope using the ambient illumination as light source has been proposed by Lee and Yang in 2014 [89]. The system works by placing the sample on the surface of the phone image sensor (thus removing the lens module is needed) and capturing direct shadow images under the ambient illumination. Images are acquired at different angles and reconstructed to achieve high resolution. The system has been tested with various types of green algae in freshwater.

A summary of smartphone camera sensing applications is reported in Table 2.

3. Microphone

Mobile phone embedded microphone can be used for different sensing applications, mainly related to healthcare.

Larson et al. in 2012 proposed a smartphone sensing system (SpiroSmart) to measure the lung function as a quick and low-cost tool for the diagnosis of chronic lung diseases [90]. The system is very cost-effective if compared to a commercial clinical spirometer and works as follows: the user holds the mobile phone at approximately arm's length, breathing in full lung volume and exhaling at the phone screen. The microphone records the exhalation sound (sampling at 32 kHz), processes the acquired data, extracts some feature parameters from the processed data and calculates the breath flow curve using a machine learning algorithm. Some key parameters such as Forced Vital Capacity (FVC), Forced Expiratory Volume (FEV) and Peak Expiratory Flow (PEF) can be calculated to estimate the user lung status. The proposed system has been tested with 52 subjects and the results have shown that the average error, if compared to a commercial spirometer, is 5.1% and can be reduced to 4.6% if the system is calibrated on the particular user. The same authors in 2013 proposed another system (SpiroCall) that can be run on any mobile phone (and not only smartphones) [91]: in this case the audio data are acquired by the phone microphone and then transferred to a server for processing. The results have shown that the accuracy is only slightly worse than SpiroSmart, with an average error of 8.01% if compared to a commercial spirometer.

The same research group in 2011 proposed a smartphone based system for cough sensing [92]: the user carry the phone in the shirt pocket or using a neck strap and audio data are recorded continuously (sample rate 32 kHz). The recorded data are processed with Pricipal Component Analysis (PCA) algorithm and machine learning to detect and count the number of coughs occurring in a certain time period. The system has a privacy protection feature to allow cough sound (but not speech) to be reconstructed. Tests on 17 subjects (from 18 to 60 years old) have shown how if a number of PCA components of 15 is used, the system can detect and reconstruct cough sound while making speech sound unintelligible.

A smartphone based respiratory rate sensor system was discussed in 2016 by Nam et al. [93]. The system records nasal and tracheal breath sounds using the phone microphone at 44.1 kHz. Acquired data are pre-processed and analyzed with two different methods: Welch periodogram technique and

autoregressive power spectral analysis. Tests on 10 subjects showed that an estimation error lower than 1 % can be achieved in the case of respiratory rates in the range 6 – 90 breaths/min and nasal breath sound analysis.

Chen et al. in 2012 proposed a phone based system to detect nasal symptoms (such as runny nose, stuffy nose and sneezing) in a real environment [94]. The system, tested on 21 subjects, records the sounds using the phone microphone and then transfers the acquired data to a remote server for processing.

A smartphone based system to quantify snoring and sleep apnea severity was discussed by Nakano et al. in 2014 [95]. Snoring sound was acquired in 0.1 s windows every 0.2 s (acquisition rate 11025 Hz) and processed with Discrete Fourier Transform. The results have shown a good correlation (> 0.9) with reference methods.

Na et al. in 2014 presented a smartphone based system to measure a subject hearing threshold in a real noisy environment [96]. The system acquires the environmental noise with the phone microphone and fits it to one of two different models, white noise or babble noise. The user is then asked to listen a set of single frequency tones (500, 1000, 2000 and 4000 Hz) and the hearing threshold is calculated and compensated based on the environmental noise. A smartphone based hearing screening system was also proposed by Swanepoel et al. in 2014 [97]. Test on 162 children were performed generating tones at 1, 2 and 4 kHz using the phone speaker and the noise environment detected by microphone. A 97.8 % agreement with reference hearing screening methods was found.

Wang et al. in 2017 developed a tremor detection system based on smartphone for the early diagnosis of Parkinson's disease [98]: the phone, placed on a table near the user hand, generates non audible sound waves in the frequency range 16.8 – 21.7 Hz using the embedded speaker and the reflected waves are acquired by the microphone with a sampling rate of 48 kHz. The tremor (magnitude and frequency) was detected by measuring the phase of the reflected wave and an app was developed to present the results to the user.

The smartphone embedded microphone was also used by Siegel et al. in 2017 to detect occlusions in automotive engine air filters [99]: the audio, recorded to an uncompressed stereo WAV file at 48 kHz, was processed with machine learning algorithms using Discrete Fourier Transform (DTF), Discrete Wavelet Transform (DWT) and Mel-Frequency Cepstral Coefficients (MFCC) and a detection rate of 81% was achieved.

Li et al. in 2017 proposed a smartphone system to detect approaching cars for the purpose of pedestrian safety and traffic monitoring [100]: audio was acquired with the phone microphone, pre-processed with 0.5 s time windows and analyzed with DFT. The extracted feature was the maximal frequency component that crosses a threshold. Different car models and size as well as different outdoor environments were tested and a detection rate of 91 % was achieved for cars that are more than 4 seconds away from the user. The authors showed that, using a second microphone, also the car direction and the number of cars can be estimated and in this case a detection rate of 81 % was obtained.

The phone microphone has been used also in applications not related to audio recording. For example, Petersen et al. in 2013 proposed a smartphone based pulse oximeter [101]. The device principle of work is sketched in Fig. 3 (a) and (b): a couple of LEDs (910 nm infra-red LED and 660 nm red LED) irradiate the finger of the subject under test and a photodiode, on the other side, measures the radiation intensity transmitted through the finger. From the absorbance at the two wavelengths the oxygen saturation and heart rate are calculated. The two LEDs are driven by the phone audio port and the current through the photodiode, proportional to the incident radiation, is converted to a voltage by a JFET amplifier and acquired by the microphone (sampling rate 8 kHz). The developed system, shown in Fig. 3 (c) and (d), has been tested using a patient simulator and the achieved correlation was found higher than 0.99.

Another microphone application not related to audio recording was proposed by Broeders et al. in 2013 [102]: an impedance biosensor was built from a test strip, coated with a sensing layer, where the analyte under test is placed; a sine-wave input voltage is applied to the biosensor electrodes and

the drawn current is measured, thus calculating the sensor impedance. The input stimulus is generated with the phone audio speaker and the current is converted to a voltage and measured with the microphone. The system, capable to perform impedance measurements between 100 Ω and 10 k Ω in the frequency range 20 Hz – 20 kHz, has been used to measure histamine concentration in phosphate buffer saline (PBS) solution.

A summary of smartphone microphone sensing applications is reported in Table 3.

4. Accelerometer, gyroscope, magnetometer and GPS

Global Positioning System (GPS) is a radionavigation system based on the measurement of the time needed for the signal to cover the distance satellite-receiver. It was developed in 1973 by US government for military applications and more recently allowed to be used for civilian use. It is nowadays embedded in almost every smartphone since it can support different applications mainly related to geo-localization and assisted navigation. Blanke et al. in 2014 presented an application for crowd dynamics monitoring using the GPS embedded in the smartphone [103] where 28000 users were monitored during a 3 days event in Zurich. A similar application was proposed by Wirz et al. and tested during the Lord Mayor's Show in London in 2011 [104]; Charlton et al. proposed an application for bicycle tracking [105]; Whipple et al. presented an application based on GPS and Google search to help safety driving [106], providing an alarm when the driving speed exceeds a legal threshold inside a school zone.

Smartphone embedded accelerometer, gyroscope and magnetometer are used inside a wide range of applications, mainly related to activity recognition, structural health monitoring, as well as driving style recognition and road condition monitoring.

Activity recognition applications are carried out using the following principle of work: the sensors output is sampled and grouped in a set of time windows, each characterized by a certain number of samples; the acquired data are processed and some feature parameters are extracted (such as average window value, peak-to-peak amplitude, interpeaks frequency, etc.); the feature parameters

are used inside a classification algorithm (either based on threshold comparison or machine learning) and the activities classified according to the results. Different examples of activity recognition applications with smartphone have been presented in literature. Guiry et al. used the phone accelerometer and an external accelerometer (tied to the subject chest and communicating with the phone by Bluetooth) to discriminate different activities such as walking, running, cycling, sitting, standing, lying [107]: in the first trial 6 subjects were tested using only the phone 3-axis accelerometer and achieving an accuracy of 88%, while in the second trial both accelerometers were used by 24 subjects with an accuracy in classification of 98%. Bieber et al. used the smartphone 3-axis accelerometer to discriminate between stand-up and sit-down transition [108]: 12 subjects were tested with the phone in their trousers and the accelerometer sampled at 20 Hz, leading to a recognition rate of 70% (the type of weared trousers affected the classification accuracy). Bayat et al. exploited the phone accelerometer to test 4 subjects with the phone in their hand or pocket and classified six activities (slow walking, fast walking, running, stairs-up, stairs-down, dancing) [109]. The accelerometer was sampled at 100 Hz and the achieved accuracy was 91.15%. Kwon et al. used the 3-axis accelerometer and 3-axis gyroscope embedded in the smartphone (carried in the trouser pocket) to classify 5 physical activities [110]. Each activity was monitored for 10 minutes with a sampling rate of 50 Hz and a detection rate higher than 90% was obtained. Shoaib et al. used accelerometer, gyroscope, magnetometer and linear accelerometer to discriminate seven physical activities (walking, running, sitting, standing, jogging, biking, walking upstairs, walking downstairs) [111]. Ten subjects were tested with the phone in five different positions, data acquired at 50 Hz with 2 seconds time windows and 50% overlap. The results have shown how gyroscope performs better than accelerometer to discriminate walking upstairs and downstairs, while the magnetometer needs proper features to be selected for accurate discrimination. Ghosh and Riccardi used the smartphone accelerometer and gyroscope (both sampled at 40 Hz) and the microphone (sampled at 8 kHz) to discriminate 6 different activities (walking, standing, sitting, driving, travelling by bus, travelling by train) [112]. Test on 15 subjects

were carried out using 3 seconds time windows with 50% overlap and the results showed how the combination of the three sensors allows better recognition results during normal everyday usage.

A particular case of activity recognition is represented by fall detection. Fall detection systems have been investigated intensively in recent years since represent a tool to reduce the risk of long laying periods after a fall, in particular for the elderly and people with neurodegenerative diseases. Smartphone based fall detection systems are even more popular since the exploited sensor (usually the 3-axis accelerometer) is integrated in the phone and thus is not intrusive as an external sensor that needs to be tied to the subject [113]. The principle of work is as follows: the user carries the phone in his trouser or pocket; when a fall is detected the phone alerts the user about the detection (vibration or sound); if the fall was correctly detected and the subject lays unconscious on the floor, after a period an alarm is sent (via Wi-fi) to call for assistance, otherwise the user can cancel the action for the misclassified fall. Tacconi et al. in 2011 proposed a system where the phone is carried on the user waist belt and a detection rate close to 100% was achieved based on tests on 3 subjects and different types of fall [114]. Zhao et al. exploited the accelerometer embedded in a Nokia N95 smartphone to detect fall based on a machine learning algorithm [115]. Ten subjects were tested while performing 4 types of activities (standing, walking, running and falling). The achieved detection rate was 98.4% where the only fall misclassification was due aggressive running. He et al. used the phone accelerometer with sampling rate 40 Hz to detect fall and send a MMS alarm with GPS coordinates when the fall is detected [116]. Dzeng et al. in 2013 used the smartphone integrated accelerometer and gyroscope to detect fall portents [117]. The application is aimed to prevent falls in the construction industry where fall accidents can lead to serious injuries and deaths. The mobile phone is tied to the subject as shown in Fig. 4 (a). The experiment environment is shown in Fig. 4 (b), (c), (d) and (e). Two different experiments were carried out. In the first experiment the fall detection was tested for six different types of falls and the detection rate was 100%. In the second experiment the detection of fall portents (i.e. dangerous situations) was tested

for different status of the subjects under test (normal, sleepiness, fatigue) and the achieved detection rate was 88.5%.

Inertial sensors embedded in modern mobile phones have been extensively exploited also in the field of civil engineering for the detection of seismic events and the structural health monitoring (SHM) of buildings and bridges. Dashti et al. in 2014 used the built-in smartphone accelerometer to monitor seismic events [118]: laboratory tests were carried out using a shaking table and the results compared with a commercial reference accelerometer. The smartphone accelerometer overestimates small seismic events but provides good accuracy in the case of moderate and intense seismic events. Even smartphones not rigidly connected to the shaking table provided reliable detection but better results were obtained with a high friction phone cover to prevent sliding. In 2013 Reilly et al. used accelerometer, magnetometer and GPS to estimate the phone orientation and measure the intensity and cardinal direction of a seismic event [119]. The application operates when the phone is not used (charging during the night or on the desk during workday) and a filtering algorithm is used to remove events due to phone falling or vibrating for a call. The use of smartphones in SHM applications is very interesting since classical SHM systems are expensive for installation and maintenance and this prevents its application in large scale to many civilian structures. Kong et al. in 2018 investigated the use of smartphone accelerometer to measure the mechanical oscillation amplitude and natural frequency of the Millikan library in Pasadena, California (USA) [120]. The building oscillations were induced using a Kinometrics model VG-1 synchronized vibration generator mounted on the roof of the building. 25 different smartphone models (embedded accelerometers of different quality) were tested against a commercial 3-axis accelerometer and a good correlation was found. Feng et al. in 2015 investigated the use of the embedded accelerometer in different smartphone models for SHM applications [121]. Tests were carried out using a shaking table (vibrations of frequencies 0.5, 0.8, 1.2, 5, 10, 20 Hz), with a masonry column model excited with operational and earthquake vibrations, as well as on a concrete pedestrian bridge. In all cases a good correlation with a commercial accelerometer (PCB 393B04) was found. Yu et al. in 2015

compared accelerometer and gyroscope embedded in the iPhone with external commercial sensors and found that both are suitable for vibration monitoring and cable force tests [122].

Another smartphone application widely investigated is related to intelligent transportation systems [30][31][32] and, in particular, the detection of driving style and road conditions. Aggressive driving behavior, such as sudden braking, excessive speeding and improper lane change, is often associated with car accidents. At the same time, anomalies in road surface not only result in less comfortable driving and extra fuel consumption but also decrease driving safety and increase the chance of damages to the vehicle. Insurance companies employ electronic systems installed on the vehicle to monitor driving behavior. However, these systems are expensive and low-cost alternatives based on smartphone are very attractive. Li et al. in 2017 proposed a smartphone based system where the embedded accelerometer was used to detect driver behavior and road conditions [123]: a reorientation software algorithm was developed to switch from smartphone-based to vehicle-based coordinate system. Acceleration along the three axis was used to detect sudden acceleration/break, lane change and bumpy road. A threshold based detection algorithm was used as well as a scoring system (ISO 2631) to estimate the seriousness of driving behavior and road conditions. In 2016 Li et al. used the phone embedded accelerometer and gyroscope to detect driving behavior with a detection rate higher than 90% [124]. Yu et al. used the accelerometer, gyroscope and magnetometer to discriminate six different driving behaviors using Support Vector Machine (SVM) and Artificial Neural Network (ANN) [125]: the training was carried out with 6 months driving traces from 20 drivers and 16 features extracted from the raw data. The validation phase, carried out on 4 months driving traces with the same drivers, resulted in a detection rate of 95.36% for SVM and 96.88% for ANN. Accelerometer, gyroscope and magnetometer were also used by Tecimer et al. in 2015 to discriminate four classes of driving behavior with a detection rate of 91% [126]. Johnson and Trivedi in 2011 exploited the rear facing camera, accelerometer, gyroscope and GPS of an iPhone 4 for driving style recognition [127]: accelerometer and gyroscope were used to discriminate 12 different driving behaviors using dynamic time warping algorithm,

GPS was used to measure speed and position while the camera for video recording. Bhoraskar et al. used the phone embedded accelerometer, magnetometer and GPS to discriminate between smooth and bumpy roads and the detection of braking events [128]. A similar application was developed by Allouch et al. by using the machine learning classification algorithm C4.5 with accelerometer and gyroscope (sample rate 50 Hz) and a detection rate of 98.6% (96.7% if using only the accelerometer) was achieved in the discrimination between smooth and bumpy roads [129]. Seraj et al. proposed a system (RoADS) based on smartphone accelerometer, gyroscope and GPS to detect road surface anomalies [130]: collected data were filtered and features extracted from time domain, frequency domain and wavelet transformation domain. A SVM classifier was used and a detection rate of about 90% was achieved regardless of vehicle type and road location.

A summary of smartphone sensing applications exploiting accelerometer, gyroscope, magnetometer and GPS is reported in Table 4.

5. Interfacing with external sensors

There are applications where the required sensors are not integrated in the mobile phone or the integrated sensors performance is not adequate. In this case external hardware must be designed to perform all the sensing tasks and communicate the results to the smartphone. This is usually implemented using a microcontroller based electronic board: the external sensors are interfaced to the microcontroller using conditioning circuits (filters, amplifiers, etc.) and analog-to-digital converters (ADC), eventually integrated inside the microcontroller, to convert the sensors analog signals to digital format. The microcontroller is also responsible for the communication with the smartphone. This can be achieved with either wired or wireless communication.

5.1 Wired communication

Wired communication methods exploit a set of electrical wires connecting the external hardware to the smartphone.

The most popular wired communication method is USB. Many recent mobile phones implement the USB On-the-Go (USB OTG) interface that allows the phone to act either as a host (making it capable to provide the power supply) or as a device [131]. USB OTG enabled smartphones can be interfaced with a large variety of USB devices (USB flash drive, digital camera, mouse, keyboard) as well as any ad-hoc designed electronic board that supports the USB interface. When acting as a host the smartphone can provide a power supply of 5V with a maximum current of 500 mA, thus allowing the external hardware to work batteryless. Many examples of sensors systems interfaced to smartphones by USB OTG have been presented in literature. Le et al. in 2016 presented a low-cost mobile electrocardiograph (ECG) using two silver coated dry electrodes [132]. Each electrode signal is fed to an operational amplifier in follower configuration and then to a differential amplifier; the resulting analog voltage is digitized by the ADC embedded inside the microcontroller MSP430 (10 bit, 1 kHz sampling rate) and then analyzed; the processed data are transferred to the smartphone by USB OTG interface. A study has been carried out on 30 subjects (between 14 and 60 years old) and the measured heart rate has been compared with the value obtained with a commercial ECG meter (Omron HEM-7111). The results show a very good correlation ($R^2 = 0.99$). A lab-on-a-chip to measure the concentration of the malaria biomarker PfHRP2 was discussed by Ghosh et al. [133]. A microfluidic chip, loaded with the sample, emits a chemiluminescent light and its intensity is detected by a photodiode, converted to voltage and processed. The results have shown a LOD of 1.2 ng/mL and a very good correlation ($R^2 = 0.99$) between the light intensity and the antigen concentration. Dou et al. discussed a 3-electrodes amperometric immunosensor for detection of clenbuterol that features a linear response in the concentration range 0 – 100 ng/mL, a LOD of 0.076 ng/mL and a time response of 6 minutes [134]. The same research group used the 3-electrodes amperometric system for gender verification in human serum and serum stains, achieving excellent sensitivity and specificity and a time response of 20 minutes [135]. A portable embedded system for contactless measurements of metals electrical conductivity and lift-off was presented by Rodrigues et al. in 2017 [136]. The sample conductivity and lift-off are measured by a coil probe

with ferrite inside that is stimulated by a sine-wave voltage signal (30 kHz). The probe impedance is function of the sample conductivity and lift-off due to the eddy currents generated in the metal. The system features an USB port to communicate with a PC or a smartphone. Aymerich et al. in 2018 presented a smartphone based micro potentiostat that performs chronoamperometry and cyclic voltammetry measurements using a 3 electrodes system [137]. The system exploits USB-OTG for power and communication and can detect alcohol in blood samples in the concentration range 0 – 1.25 g·L⁻¹.

Sometimes the smartphone USB port is used only to provide power to the sensor system while data acquisition is carried out exploiting some other sensors embedded in the phone. Such an example is presented by Doeven et al. [138]: an electrochemiluminescence sensing system to measure the emission properties of water soluble iridium complex is powered by the phone USB port and the square wave voltage to induce chemiluminescence is generated by the phone audio channel and LM567 IC. The emitted light is detected by the phone embedded camera by analyzing the RGB components of the acquired image. A USB powered electrochemiluminescence sensor was also proposed by Li et al. in 2018 for the detection of nitroaromatic explosives [139]. Another example was proposed by Hussain et al. in 2016 for a water turbidity sensing system for smartphone [140]. The phone USB port provide power to drive an infra-red LED (peak wavelength 870 nm) whose radiation is transmitted through the sample; the turbidity is estimated from the scattered light at 90° angle that is detected by the phone integrated proximity sensor. The same system with minor modifications was also used to detect other water contaminants: iron(II) in the concentration range 0 – 5 mg·L⁻¹ using a 510 nm peak wavelength LED and phosphate in the concentration range 0 – 3 mg·L⁻¹ using a 880 nm peak wavelength LED [141]. The same research group developed also other smartphone based optical sensing systems for the analysis of water: a system for the estimation of mercury level concentration, based on fluorescence emission detected by the phone camera, [142] and two systems, exploiting the phone flash LED to generate the radiation and the embedded light

sensor for detection, to measure the fluoride level in drinking water [143] and the salinity level in oceanic water environment [144].

The main drawback of using the smartphone USB port for power supply and communication is due to the fact that connector standards vary among producers of mobile phones: USB port is used for communication in Android devices but, for example, not in the Apple iPhone that used a 30 pin connector for communication until 2012 (now replaced by the 8 pin Lightning connector). Moreover only the high-end Android smartphones features the USB-OTG interface while the others can only operate in device mode and thus the external hardware power must be supplied by batteries. Connecting a USB device to a smartphone results also in reduced phone battery life since the USB device maintains the phone awake and because of USB device own power consumption. At this regard, Veen et al. in 2017 proposed a USB switch controlled by the audio port that can reduce power consumption by 47 % [145].

To provide a more standard port for power supply and wired communication with external hardware, some authors have proposed an interface based on the phone audio jack [146]. The working principle of this technique is shown in Fig. 5. A standard 3.5 mm audio jack has four terminals: the left and right audio channels, the common ground and the microphone input. The power is harvested from one of the two audio channels (left channel in Fig. 5) that generates a small voltage tone (few tens of mV) in the audio range (20 Hz – 20 kHz); this tone is boosted with a transformer, rectified and finally the power supply voltage for the external board V_{DD} is generated by a voltage regulator. The communication between the smartphone and the microcontroller is realized with the other audio channel (from smartphone to microcontroller) and the microphone (from microcontroller to smartphone). Since both the audio channels and the microphone block low frequency signals, the communication is carried out with frequency shift keying modulated packets, where the information is contained in the frequency of the signal for each packet (few ms of duration).

Many smartphone based systems exploiting the audio jack for power supply and communication have been proposed. Sun et al. discussed an electrochemical biosensor with peak power consumption of 5.7 mW and cost less than 30 USD that makes cyclic voltammetry measurements with potassium ferro-/ferricyanide [147]. A pH sensor system to monitor pulmonary exacerbations in cystic fibrosis patients has been proposed by the same research group in 2017 [148]. The system is based on the potentiostat IC LMP91200 by Texas Instruments, interfaced with two different types of pH electrodes (glass pH electrode and iridium oxide screen printed electrode) and a thermistor to compensate measured pH value due to temperature variations. The system has been tested both with PBS solutions with pH in the range 5.9 – 8.08 and patient sputum samples. Other examples include electrochemical sensing systems for the detection of Hepatitis C core antibody with a LOD of 12.3 pM [149], to measure nitrate concentration in NaOH [150] and to measure the glucose concentration in a liquid sample [151]. Nemiroski et al. in 2014 proposed a portable electrochemical detector capable to perform different electroanalytical techniques (chronoamperometry, cyclic voltammetry, differential pulse voltammetry, square wave voltammetry and potentiometry) to measure different types of analyte [152]. Jiang et al. in 2017 presented a smartphone based sensor system performing electrochemical impedance spectroscopy measurements in the frequency range 17 Hz – 17 kHz [153].

The use of the 3.5 mm audio jack for power and communication is not, however, without problems. First of all, the maximum power that can be provided by the smartphone from the audio jack is much lower than USB and varies greatly among different phone models [146]. Moreover, an always greater number of smartphone producers remove the analog audio jack to replace it with wireless solutions, thus, in a couple of years, this interface will not probably be a standard as it was in the past.

A summary of smartphone sensing applications exploiting wired communication interface with external hardware is reported in Table 5.

5.2 Wireless communication

The trend in the electronic industry is to migrate from wired to wireless communication interfaces and, from this point of view, the smartphone interfacing to external hardware is no exception. Modern mobile phones feature different types of wireless communication technologies: Wi-fi for long communication range (over 100 m), Bluetooth for short communication range (typically in the order of 10 m) and, in the case of high end smartphones, Near Field Communication (NFC) for very short range (10 cm).

Currently, the most used protocol to interface the smartphone with external hardware in the development of low-cost portable sensing systems is Bluetooth (BT). It has been used in many smartphone sensing systems for a wide range of applications, from healthcare to environmental monitoring, from home security applications to biosensor systems. In the case of BT communication, however, the designed electronic board must feature its own source of power, i.e. batteries, that need to be regularly recharged or replaced.

An example of BT technology used in smartphone healthcare applications was proposed by Dinh for a heart activity monitoring device [154]: the system, embedding a PIC microcontroller by Microchip and powered by a rechargeable 3.7 V Li-Pol battery, features ECG electrodes as well as a 3-axis accelerometer (MMA7260QT by Freescale). A similar system for cardiovascular disease detection that features a SD card for long time continuous recording was proposed by Oresko et al. [155]. Lin et al. discussed a blood pressure monitoring system capable to perform a variety of measurements (pulse rate, systolic blood pressure, diastolic blood pressure) that communicates with smartphone via Bluetooth Low Energy (BLE), a BT based technology that provides much reduced power consumption while maintaining the same communication range [156]. Keith-hynes et al. in 2014 proposed a smartphone based system for real-time control of blood glucose [157]: the smartphone runs on a modified Android OS removing all unnecessary features (like phone and text messaging) and communicates by BT with a commercial continuous glucose meter and an insulin pump. A variety of commercial glucose meters interfaced to smartphone by BT were presented by Cappon et al. in 2017 [158]. Postolache et al. proposed a wrist bracelet for telecare assessment

[159]: the system, based on PIC24F microcontroller features a pulse oximeter (realized with two LEDs and a photodiode) to measure the blood oxygen saturation and a ADXL335 3-axis accelerometer to monitor the patient motion activity; data are transferred to smartphone by BT where are processed and then sent to a web site by Wi-fi. A smartphone based system to detect fall events was discussed by Bianchi et al. [160]: the electronic board, based on the microcontroller MSP430F149 and powered by a Li-Pol rechargeable battery, hosts a 3-axis accelerometer (sampling rate 40 Hz) and a barometric pressure sensor (sampling rate 1.8 Hz): the classification is carried out with a fixed threshold algorithm and the detection sensitivity and specificity was found 97.8% and 96.7%, respectively.

In the field of environmental monitoring smartphone based sensing systems exploiting BT for communication has been also proposed. Zappi et al. proposed an air quality monitoring sensor node based on the microcontroller ATMEGA1284p and powered with a rechargeable 7200 mWh Li-ion battery [161]: the system hosts three digital sensors (temperature, humidity and barometric pressure) and three electrochemical gas sensors to detect CO, NO₂ and O₃. Once acquired by the smartphone, data are processed and sent to a remote server. Another air quality sensor system, based on the microcontroller ATMEGA168 and measuring temperature, humidity, light and CO₂ concentration, was developed by Jiang et al. [162].

Other applications exploiting BT communication are a smartphone based home security system [163], a mobile system for sensing non-speech body sounds [164] and an electroanalytical platform capable to discriminate honey samples according to bothanical and geographic origins, based on voltammetric measurements with a 3 electrodes system and PCA processing [165]. An interesting application in the field of bacterial biosensors was proposed by Jiang et al. in 2014 [166]. The system, shown in Fig. 6 (a) and (b), is based on the Arduino UNO development board and the AD5933 IC: AD5933 is a low-cost impedance analyzer on chip, interfaced with the microcontroller by Inter Integrated Circuit (I²C) port, capable to perform Electrochemical Impedance Spectroscopy (EIS) measurements [167] without expensive external instrumentations. EIS measurements were

carried out with a pre-concentrating microfluidic device on samples contaminated with different concentrations of *Escherichia coli*. The measured impedance spectrum has been modeled with the electrical circuit of Fig. 6 (c) (Randle's model) and the bacterial concentration was found to be function of the charge transfer resistance R_{ct} (decreasing for increasing contamination). A LOD of 10 CFU/mL was found. The same research group used the same system with minor modifications also for the detection of 2,4,6-trinitrotoluene (TNT) [168] and to detect proteins for point-of-care testing [169]. A smartphone based EIS measurements system, this time for the bioelectrical analysis of human body to estimate body fluids compartments, was proposed by Choi et al. in 2015 exploiting a 4 electrodes system (2 drive electrodes and 2 sense electrodes) [170]. A novel system for rapid, non-destructive testing of fruit ripeness, shown in Fig. 7, was developed by Das et al. in 2016 [171]. The system, based on Arduino pro mini development board, estimates the ripening state of different varieties of apples by measurement of UV fluorescence from the Chlorophyll present in the fruit skin. A UV LED irradiates the fruit skin and the reflected radiation optical spectrum is measured by the embedded C12666MA IC, a low-cost spectrophotometer on chip for the wavelength range 340 to 780 nm. The peak intensity of Chlorophyll emission at 680 nm was related to the photosynthetic activity and ripening. The same research group also developed a mobile phone based mini-spectrophotometer for rapid screening of skin cancer [172].

While BT is the most used technology for wireless communication between a smartphone and an external electronic board, an alternative is represented by NFC. NFC is a wireless technology based on Radio Frequency Identification (RFID) operating in the high frequency band at 13.56 MHz and supporting a maximum data rate of 424 kbit/s [173] that can read passive NFC tags when the NFC reader is in close proximity (10 cm or less). An increasing number of smartphones, in particular high-end devices, integrate a NFC reader since this technology provides many easy ways for business and transactions [174], such as for example in the mobile payments [175], to implement a mobile virtual coupon system [176][177] and in tourism applications [178].

Smartphone based sensor systems that communicate with external hardware by NFC can be classified in two different groups: passive and semi-passive [179]. Passive NFC systems are batteryless and the energy to power the external hardware is provided by the NFC reader (smartphone) by inductive coupling power transfer. Then, in passive NFC systems the measurements are carried out only when the smartphone is in close proximity to the system. Semi-passive NFC systems, on the other hand, are battery powered and this allows the system to perform measurements at regular time intervals. These measurements are stored on some on-board memory and sent to the smartphone during the NFC transfer. Examples of semi-passive NFC systems are those devoted to food traceability [180] where some parameters (such as temperature and humidity) must be measured regularly and independently on the presence of the NFC reader in close proximity.

Kassal et al. in 2013 presented a semi-passive sensor system for potentiometric measurements [181]. The system was built around the IC SL13A (now obsolete and replaced by SL900A), an ultra low power RFID transponder capable to operate both in passive or semi-passive mode featuring internal 8 kbit EEPROM, real-time clock, an internal temperature sensor and input for an external sensor. The device is powered with a 3V lithium coin cell and interfaced with a pH electrode. Measurements were carried out at time intervals of 10 minutes on phosphate buffer solutions (for 5 days) and fresh goat milk (for 6 days). The measured data produced an accuracy of 0.01 and precision of 0.03 if compared with a commercial pH meter. The same system with minor modifications has been interfaced with commercial test strips for glucose concentration measurements [182] and used to design a smart bandage with screen printed electrodes for the measurement of uric acid concentration [183]. The same research group in 2018 also developed a wireless fluorimeter based on smartphone [184]: the system, powered by a 3V lithium coin cell, performs fluorescence measurements using a LED and a photodiode and communicate with the phone by NFC using a MLX90128 transponder. This highly adaptable system has been tested for liquid analysis (detection of fluorescein in the concentration range 10^{-7} to 10^{-5} M using a 502 nm

LED) and paper based sensing (detection of chloride concentration in the range 1 – 100 mM using a 355 nm UV LED). Magno et al. in 2016 designed a wearable smart bracelet that embeds a 3-axis accelerometer, an analog microphone, an analog 112x112 pixels camera and a temperature sensor [185]. The system, powered from a 40 mAh 3.7V Li-Pol rechargeable battery, is based on the microcontroller MSP430FR5969 (16 Mhz) and can communicate with a smartphone by NFC. To avoid the need of battery recharge or replacement an energy harvesting system is present that scavenges power from the embedded solar panels and thermoelectric generator modules.

A compact dosimetric system based on passive NFC tag and smartphone was proposed by Carvajal et al. in 2017 [186]. The system measures dose of an ionizing radiation and was tested by irradiating a commercial DMOS transistor ZVP3306 with photon beam of 6 MV up to 20 Gy. The developed system is batteryless and harvests the power source from the electromagnetic field coming from the smartphone NFC link. In Fig. 8 (a) the schematic of the system is shown: the transistor source current is provided by the IC LM334 and the transistor threshold voltage shift (function of the radiation dose) is measured from the source voltage level. The source voltage is conditioned to be in the range 300 to 600 mV and acquired by the RFID transponder SL13A. The achieved sensitivity is 4.75 ± 0.15 mV/Gy. A picture of the sensor tag and module are shown in Fig. 8 (b) and (c) while a picture of the whole system is represented in Fig. 8 (d). Another passive NFC based sensor was proposed by Rose et al. [187]. The system is an adhesive sensor patch embedding electrodes to monitor sweat electrolytes: Na^+ concentrations from 10 to 90 mM were tested and a correlation of $R^2 = 0.92$ was found. The proposed tag is based on the IC MLX90129, a RFID transponder working at 13.56 MHz, that, similarly to SL13A, can work both in passive and semi-passive mode, has an internal temperature sensor, can be interfaced to external resistive sensors and, in addition, features a SPI interface that can be used to communicate with a microcontroller. A battery-less enzymatic amperometric glucose sensor based on NFC technology was also discussed by Matoschitz et al. [188]. Boada et al. in 2018 designed a passive NFC device for the measurement of soil moisture [189]: the system, based on the Atmel low-power microcontroller ATtiny85, is interfaced with a

temperature and an humidity sensor and an interdigitated capacitive sensor for the measurement of soil volumetric water content (VWC). The system power (1 mA at 3.3 V) is provided by the M24LR04E-R NFC transponder (interfaced with an ad-hoc designed antenna) that harvests the energy from the smartphone. Good correlation with commercial sensors was achieved once the system was calibrated in the VWC range 0 – 50 %.

An unconventional NFC based sensing system was discussed by Xu et al. in 2017 [190]. The working principle, as shown in Fig. 9 (a), is based on the fact that commercial NFC tags are realized with a RLC circuit and the resistance component R_{iC} is characterized by a threshold R_{TH} that discriminates the ability to read the tag, i.e. when the smartphone is in close proximity the tag is readable only if $R_{iC} < R_{TH}$. Thus the authors cut a section of the conducting aluminium film and placed an element in series to R_{iC} whose resistance is function on the analyte of interest. The modified sensor gives a binary output, i.e. it can determine if the analyte concentration is higher or lower than a certain threshold. The measurement resolution can be increased by creating different replicas of the tag, each with a different value of the threshold, by changing the value of R_{iC} . This is shown in Fig. 9 (b) where five different replicas of the tag are created to measure different concentration of ethanol. The proposed system has been successfully tested also for gas detection and the measure of bacterial concentration. The same working principle was also discussed by Azzarelli et al. for the concentration measurement of four different analytes (NH_2 , cyclohexane, H_2O_2 , H_2O) [191] and by Ma et al. in 2018 for the measurement of different biogenic amines for food spoilage detection [192].

A summary of smartphone sensing applications exploiting wireless communication interface with external hardware is reported in Table 6.

6. Prospects and Challenges

The strong diffusion of smart mobile phones in the last years and the introduction of application delivery channels, where apps can be downloaded by smartphone users, have produced a change in

the sensing applications. In addition to traditional personal sensing systems, i.e. applications where a single device is involved, innovative mobile crowdsensing applications have been introduced [33][34][193]. In crowdsensing applications many smartphone users acquire data that are sent to a cloud server where are processed and the results released to the public in the form of aggregated data and statistics, for example using social networks. Data acquisition in crowdsensing application can be carried out either with the internal smartphone sensors or using external sensors: the second choice is however used only for projects with a small number of participants, since this results in increased costs per user. Crowdsensing applications can be classified as participatory or opportunistic [194]. In participatory applications the user is responsible for data acquisition (for example taking a photo or making a measurement). In opportunistic applications, instead, the user is only asked to start the application while data acquisition is carried out automatically at regular time intervals. Both types of application have advantages and drawbacks. In the case of participatory sensing, the frequency of data acquisition can be the result of the user interest in participating the project. This problem does not affect opportunistic sensing (where sensors data are acquired at regular time intervals) but, in this case, data quality can be reduced if sensors are measured at the wrong moment (for example a microphone is acquired when the phone is in the user pocket or in a noisy environment). Examples of crowdsensing applications are, for example, SecondNose [195], where an external air pollution sensor, interfaced by BT with the smartphone, collects environmental and air pollution parameters, or Pazl [196], a Wi-fi based indoor monitoring system. Programming framework to develop crowdsensing applications on smartphone have been also proposed [197][198].

Another type of application that is gaining popularity is persuasive sensing, where collected data are analyzed and presented to the user not only to inform but also to persuade to change behavior by using on-screen animations or simple games. Examples of smartphone based persuasive sensing applications are: BeWell [199] that exploits the phone accelerometer and microphone to monitor sleep, physical activity and social interaction and presents the results in the form of an aquatic

ecosystem animation displayed on the phone lock-screen and wallpaper; Sensing Fork [200] that interfaces the phone by BT with an external accelerometer, electrodes and color sensor to detect the eating behavior of children and try to motivate them using an integrated game; UKKO [201] that, using a commercial environmental sensor interfaced by BT and the phone GPS, monitors children route in walking to school and promotes healthy walking using an integrated virtual pet game.

Despite the increasing interest in smartphone based sensing systems, there are also some gaps that need further research. The major challenges are represented by the energy consumption and, in the case of crowdsensing applications, the privacy concerns. The energy consumption is a big problem since a quick depletion of the phone battery has a strong impact on the willingness to use the application. The advance in smartphone sensing system is characterized by the adoption of multi-sensors fusion techniques [202][203] and computationally intensive deep learning algorithms [204][205] that contribute to increase the energy consumption problem. At this regard, power management [206] and optimization techniques [207] have been proposed to save energy [208]: for example not all sensors are characterized by the same power consumption (camera and GPS are more power expensive than accelerometer) and the choice of the correct sensor as well as a lower sampling rate can help to mitigate the problem. In the case of crowdsensing application, power saving can be achieved also by the implementation of the most computationally intensive algorithms on the cloud server and the use of low-power wireless networks. The use of energy harvesting techniques to scavenge power from natural energy sources such as solar [209] and thermal [210] can also help to extend battery life. The privacy problem is important in particular for crowdsensing applications, where the participating users share personal data. Most privacy concerns are related to data from camera, microphone and GPS. However, recent investigations have shown how other phone sensors can also produce privacy violations: for example Liang et al. have used the smartphone accelerometer and a deep-learning algorithm to detect tap position on the screen and thus infer apps usage habits and passwords [211]. Different techniques to protect the user privacy have been proposed in literature [212][213][214].

7. Conclusions

A survey of measurement and sensor systems development using modern mobile phones has been presented. The exploitation of smartphone as a sensing system is gaining always more interest due to the strong computing capability, rich set of embedded sensors and integrated wired and wireless communication technology.

The recent large diffusion of smartphones even in developing countries represents an opportunity for the development of low-cost sensor systems, in particular in the field of healthcare, point-of-care diagnostic and food analysis, to provide services in places lacking the access to diagnostic laboratories and expensive instrumentation. In addition, the pervasive computing and large mass storage memories available in modern mobile phones allow the implementation of computational intensive machine learning algorithms in crowdsensing applications where big data are acquired from a large number of users.

Two different approaches in the design of smartphone based sensing systems have been discussed. The first, based on the exploitation of the large number of sensors embedded in the device, is the most appealing since allows the system development using already available hardware, thus minimizing the cost of the system. Sometimes, however, the required sensors are not available in the phone or the sensor performance does not meet the requirements. In this case external sensors must be added and interfaced with ad-hoc designed external hardware (usually based on microcontroller) that communicates with the smartphone using the available wired or wireless communication technology.

The quick advance in smartphone based sensing systems is not, however, without problems. The increased computing capability and number of embedded sensors produce an increase of the phone power consumption that, in the end, results in faster battery discharge. Moreover, in the case of crowdsensing applications, where users share collected data in cloud servers, privacy concerns arise

for possible threats to the users personal information. Thus, progress in these research lines is mandatory for the future of efficient and safe smartphone based sensing systems.

References

- [1] I. Nayeem, R. Want, Smartphones: Past, present, and future, *IEEE Pervasive Computing* 13 (4) (2014) 89-92.
- [2] M. Grossi, R. Lazzarini, M. Lanzoni, A. Pompei, D. Matteuzzi, B. Riccò, A portable sensor with disposable electrodes for water bacterial quality assessment, *IEEE Sensors Journal* 13 (5) (2013) 1775-1782.
- [3] M. Grossi, C. Parolin, B. Vitali, B. Riccò, Bacterial concentration detection using a portable embedded sensor system for environmental monitoring, in: *Proceedings of the 7th IEEE International Workshop on Advances in Sensors and Interfaces (IWASI)*, (2017), pp. 246-251.
- [4] V. Villagrán, A. Montecinos, C. Franco, R.C. Muñoz, Environmental monitoring network along a mountain valley using embedded controllers, *Measurement*, 106 (2017) 221-235.
- [5] M. Grossi, G. Di Lecce, T.G. Toschi, B. Riccò, A novel electrochemical method for olive oil acidity determination, *Microelectronics Journal*, 45 (12) (2014) 1701-1707.
- [6] M. Grossi, G. Di Lecce, M. Arru, T.G. Toschi, B. Riccò, An opto-electronic system for in-situ determination of peroxide value and total phenol content in olive oil, *Journal of food engineering*, 146 (2015) 1-7.
- [7] A. Chowdhury, S. Datta, T.K. Bera, D. Ghoshal, D., B. Chakraborty, Design and development of microcontroller based instrumentation for studying complex bioelectrical impedance of fruits using electrical impedance spectroscopy, *Journal of Food Process Engineering*, (2017).
- [8] P. Santharaman, K.A. Venkatesh, K. Vairamani, A.R. Benjamin, N.K. Sethy, K. Bhargava, C. Karunakaran, ARM-microcontroller based portable nitrite electrochemical analyzer using cytochrome c reductase biofunctionalized onto screen printed carbon electrode, *Biosensors and Bioelectronics*, 90 (2017) 410-417.
- [9] K. Strzelak, N. Rybkowska, A. Wiśniewska, R. Koncki, Photometric flow analysis system for biomedical investigations of iron/transferrin speciation in human serum, *Analytica chimica acta*, 995 (2017) 43-51.

- [10] N. Rybkowska, R. Koncki, K. Strzelak, Optoelectronic iron detectors for pharmaceutical flow analysis, *Journal of pharmaceutical and biomedical analysis*, 145 (2017) 504-508.
- [11] M. Grossi, B. Riccò, A portable electronic system for in-situ measurements of oil concentration in MetalWorking fluids, *Sensors and Actuators A: Physical*, 243 (2016) 7-14.
- [12] M. Grossi, B. Riccò, An automatic titration system for oil concentration measurement in metalworking fluids, *Measurement*, 97 (2017) 8-14.
- [13] C. Budelmann, Opto-Electronic Sensor Network Powered Over Fiber for Harsh Industrial Applications, *IEEE Transactions on Industrial Electronics*, 65 (2) (2018) 1170-1177.
- [14] P. Daponte, L. De Vito, F. Picariello, M. Riccio, State of the art and future developments of measurement applications on smartphones, *Measurement*, 46 (9) (2013) 3291-3307.
- [15] M. Kakihara, Grasping a Global View of Smartphone Diffusion: An Analysis from a Global Smartphone Study. In *ICMB (2014)* p. 11.
- [16] F. Lamonaca, G. Polimeni, K. Barbé, D. Grimaldi, Health parameters monitoring by smartphone for quality of life improvement, *Measurement*, 73 (2015) 82-94.
- [17] A.S.M. Mosa, I. Yoo, L. Sheets, A systematic review of healthcare applications for smartphones, *BMC Medical Informatics and Decision Making*, 12 (1) (2012) 67.
- [18] M.M. Baig, H. GholamHosseini, M.J. Connolly, Mobile healthcare applications: system design review, critical issues and challenges, *Australasian Physical & Engineering Sciences in Medicine*, 38 (1) (2015) 23-28.
- [19] J. Behar, A. Roebuck, J.S. Domingos, E. Geder, G.D. Clifford, A review of current sleep screening applications for smartphones, *Physiological Measurement*, 34 (7) (2013) R29.
- [20] X. Xu, A. Akay, H. Wei, S. Wang, B. Pingguan-Murphy, B.E. Erlandsson, X. Li, W. Lee, J. Hu, L. Wang, F. Xu, Advances in smartphone-based point-of-care diagnostics, *Proceedings of the IEEE*, 103 (2) (2015) 236-247.
- [21] K.E. McCracken, J.Y. Yoon, Recent approaches for optical smartphone sensing in resource-limited settings: a brief review, *Analytical Methods*, 8 (36) (2016) 6591-6601.

- [22] A.S. Juarascio, S.M. Manasse, S.P. Goldstein, E.M. Forman, M.L. Butryn, Review of smartphone applications for the treatment of eating disorders, *European Eating Disorders Review*, 23 (1) (2015) 1-11.
- [23] G. Rateni, P. Dario, F. Cavallo, Smartphone-based food diagnostic technologies: a review, *Sensors*, 17 (6) (2017) 1453.
- [24] S. Pongnumkul, P. Chaovalit, N. Surasvadi, Applications of smartphone-based sensors in agriculture: a systematic review of research, *Journal of Sensors*, (2015).
- [25] D. Zhang, Q. Liu, Biosensors and bioelectronics on smartphone for portable biochemical detection, *Biosensors and Bioelectronics*, 75 (2016) 273-284.
- [26] A. Roda, E. Michelini, M. Zangheri, M. Di Fusco, D. Calabria, P. Simoni, Smartphone-based biosensors: a critical review and perspectives, *TrAC Trends in Analytical Chemistry*, 79 (2016) 317-325.
- [27] A.J. McGonigle, T.C. Wilkes, T.D. Pering, J.R. Willmott, J.M. Cook, F.M. Mims, A.V. Parisi, Smartphone Spectrometers, *Sensors*, 18 (1) (2018) 223.
- [28] J.C. Contreras-Naranjo, Q. Wei, A. Ozcan, Mobile phone-based microscopy, sensing, and diagnostics, *IEEE Journal of Selected Topics in Quantum Electronics*, 22 (3) (2016) 1-14.
- [29] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J. Havinga, A survey of online activity recognition using mobile phones, *Sensors*, 15 (1) (2015) 2059-2085.
- [30] J. Wahlström, I. Skog, P. Händel, Smartphone-based vehicle telematics: a ten-year anniversary, *IEEE Transactions on Intelligent Transportation Systems*, 18 (10) (2017) 2802-2825.
- [31] J. Engelbrecht, M.J. Booyen, G.J. van Rooyen, F.J. Bruwer, Survey of smartphone-based sensing in vehicles for intelligent transportation system applications, *IET Intelligent Transport Systems*, 9 (10) (2015) 924-935.
- [32] G. Chugh, D. Bansal, S. Sofat, Road condition detection using smartphone sensors: a survey, *International Journal of Electronic and Electrical Engineering*, 7 (6) (2014) 595-602.

- [33] R.K. Ganti, F. Ye, H. Lei, Mobile crowdsensing: current state and future challenges, *IEEE Communications Magazine*, November (2011) 32-39.
- [34] J. Liu, H. Shen, X. Zhang, A survey of mobile crowdsensing techniques: a critical component for the Internet of Things, *ACM Transactions on Cyber-Physical Systems*, 2 (3) (2018) 18.
- [35] Z. Xu, Z.D. Chen, H. Nie, Handheld computers: Smartphone-centric wireless applications, *IEEE Microwave Magazine*, 15 (2) (2014) 36-44.
- [36] S.D. Kim, Y. Koo, Y. Yun, A Smartphone-Based Automatic Measurement Method for Colorimetric pH Detection Using a Color Adaptation Algorithm, *Sensors*, 17 (7) (2017) 1604.
- [37] S. Lee, V. Oncescu, M. Mancuso, S. Mehta, D. Erickson, A smartphone platform for the quantification of vitamin D levels, *Lab on a Chip*, 14 (8) (2014) 1437-1442.
- [38] Y. Jung, J. Kim, O. Awofeso, H. Kim, F. Regnier, E. Bae, Smartphone-based colorimetric analysis for detection of saliva alcohol concentration, *Applied optics*, 54 (31) (2015) 9183-9189.
- [39] A.K. Yetisen, J.L. Martinez-Hurtado, A. Garcia-Melendrez, F. da Cruz Vasconcellos, C.R. Lowe, A smartphone algorithm with inter-phone repeatability for the analysis of colorimetric tests, *Sensors and Actuators B: Chemical*, 196 (2014) 156-160.
- [40] L. Shen, J.A. Hagen, I. Papautsky, Point-of-care colorimetric detection with a smartphone, *Lab on a Chip*, 12 (21) (2012) 4240-4243.
- [41] S.C. Kim, U.M. Jalal, S.B. Im, S. Ko, J.S. Shim, A smartphone-based optical platform for colorimetric analysis of microfluidic device, *Sensors and Actuators B: Chemical*, 239 (2017) 52-59.
- [42] Z. Liu, Y. Zhang, S. Xu, H. Zhang, Y. Tan, C. Ma, R. Song, L. Jiang, C. Yi, A 3D printed smartphone optosensing platform for point-of-need food safety inspection, *Analytica chimica acta*, 966 (2017) 81-89.
- [43] S. Dutta, G.P. Saikia, D.J. Sarma, K. Gupta, P. Das, P. Nath, Protein, enzyme and carbohydrate quantification using smartphone through colorimetric digitization technique, *Journal of Biophotonics*, 10 (2017) 623-633.

- [44] D. Bueno, R. Muñoz, J.L. Marty, Fluorescence analyzer based on smartphone camera and wireless for detection of Ochratoxin A, *Sensors and Actuators B: Chemical*, 232 (2016) 462-468.
- [45] M.A. Hossain, J. Canning, K. Cook, S. Ast, A. Jamalipour, Photo-and thermal degradation of olive oil measured using an optical fibre smartphone spectrofluorimeter, in: *IEEE 25th Optical Fiber Sensors Conference (OFS)*, (2017), 1-4.
- [46] A. Hakonen, J.E. Beves, Hue parameter fluorescence identification of edible oils with a smartphone, *ACS sensors*, 3 (2018) 2061-2065.
- [47] K.E. McCracken, T. Tat, V. Paz, J.Y. Yoon, Smartphone-based fluorescence detection of bisphenol A from water samples, *RSC Advances*, 7 (15) (2017) 9237-9243.
- [48] A.V. Parisi, N. Downs, D. Igoe, J. Turner, Characterization of cloud cover with a smartphone camera, *Instrumentation Science and Technology*, 44 (2016) 23-34.
- [49] S.K. Ahuja, M.K. Shukla, A survey of computer vision based corrosion detection approaches, *Information and Communication Technology for Intelligent Systems (ICTIS 2017)*, 2 (2017) 55-63.
- [50] D. Igoe, A.V. Parisi, Characterization of the corrosion of iron using a smartphone camera, *Instrumentation Science and Technology*, 44 (2016) 139-147.
- [51] D. Xia, C. Ma, S. Song, W. Jin, Y. Behnamian, H. Fan, J. Wang, Z. Gao, W. Hu, Atmospheric corrosion assessed from corrosion images using fuzzy Kolmogorov-Sinai entropy, *Corrosion Science*, 120 (2017) 251-256.
- [52] J.L. Delaney, E.H. Doeven, A.J. Harsant, C.F. Hogan, Use of a mobile phone for potentiostatic control with low cost paper-based microfluidic sensors, *Analytica chimica acta*, 790 (6) (2013) 56-60.
- [53] T. San Park, J.Y. Yoon, Smartphone detection of Escherichia coli from field water samples on paper microfluidics, *IEEE Sensors Journal*, 15 (3) (2015) 1902-1907.
- [54] P.S. Liang, T. San Park, J.Y. Yoon, Rapid and reagentless detection of microbial contamination within meat utilizing a smartphone-based biosensor, *Scientific reports*, 4 (2014) 5953.

- [55] Y. Matsumura, H.N. Ananthaswamy, Toxic effects of ultraviolet radiation on the skin, *Toxicology and Applied Pharmacology*, 195 (3) (2004) 298-308.
- [56] J. D'Orazio, S. Jarrett, A. Amaro-Ortiz, T. Scott, UV radiation and the skin, *International Journal of Molecular Sciences*, 14 (6) (2013) 12222-12248.
- [57] F.R. De Grujil, Photocarcinogenesis: UVA vs. UVB radiation, *Skin Pharmacology and Physiology*, 15 (5) (2002) 316-320.
- [58] O. Engelsen, The relationship between ultraviolet radiation exposure and vitamin D status, *Nutrients*, 2 (5) (2010) 482-495.
- [59] M. Rivas, E. Rojas, M.C. Araya, G.M. Calaf, Ultraviolet light exposure, skin cancer risk and vitamin D production, *Oncology letters*, 10 (4) (2015) 2259-2264.
- [60] D. Igoe, A.V. Parisi, B. Carter, Characterization of a smartphone camera's response to Ultraviolet A radiation, *Photochemistry and Photobiology*, 89 (2013) 215-218.
- [61] D. Igoe, A.V. Parisi, B. Carter, Evaluating UVA aerosol optical depth using a smartphone camera, *Photochemistry and Photobiology*, 89 (2013) 1244-1248.
- [62] D. Igoe, A.V. Parisi, B. Carter, Smartphone based Android app for determining UVA aerosol optical depth and direct solar irradiances, *Photochemistry and Photobiology*, 90 (2014) 233-237.
- [63] J. Turner, A.V. Parisi, D. Igoe, A. Amar, Detection of Ultraviolet B radiation with internal smartphone sensors, *Instrumentation Science and Technology*, 45 (2017) 618-638.
- [64] D. Igoe, A. Amar, A.V. Parisi, J. Turner, Characterisation of a smartphone sensor response to direct solar 305 nm irradiation at high air masses, *Science of the Total Environment*, 587-588 (2017) 407-413.
- [65] D. Igoe, A.V. Parisi, A. Amar, N.J. Downs, J. Turner, Atmospheric total ozone column evaluation with a smartphone image sensor, *International Journal of Remote Sensing*, 39 (9) (2018) 2766-2783.

- [66] T.C. Wilkes, T. Pering, A. McGonigle, G. Tamburello, J.R. Willmott, A low-cost smartphone sensor-based UV camera for volcanic SO₂ emission measurements, *Remote Sensing*, 9 (1) (2017) 27.
- [67] A. McGonigle, T. Pering, T.C. Wilkes, G. Tamburello, R. D'Aleo, M. Bitetto, A. Aiuppa, J.R. Willmott, Ultraviolet imaging of volcanic plumes: a new paradigm in volcanology, *Geosciences*, 7 (3) (2017) 68.
- [68] T.C. Wilkes, A.J.S. McGonigle, T.D. Pering, A.J. Taggart, B.S. White, R.G. Bryant, J.R. Willmott, Ultraviolet imaging with low cost smartphone sensors: development and application of a Raspberry Pi-based UV camera, *Sensors*, 16 (2016) 1649-1656.
- [69] S. Dutta, D. Sarma, P. Nath, Ground and river water quality monitoring using a smartphone-based pH sensor, *AIP Advances*, 5 (5) (2015) 057151.
- [70] S. Dutta, K. Saikia, P. Nath, Smartphone based LSPR sensing platform for bio-conjugation detection and quantification, *RSC Advances*, 6 (26) (2016) 21871-21880.
- [71] S. Dutta, A. Choudhury, P. Nath, Evanescent wave coupled spectroscopic sensing using smartphone, *IEEE Photonics Technology Letters*, 26 (6) (2014) 568-570.
- [72] S. Dutta, D. Sarma, A. Patel, P. Nath, Dye-assisted pH sensing using a smartphone, *IEEE Photonics Technology Letters*, 27 (22) (2015) 2363-2366.
- [73] S. Gupta, H.C. Liaw, P. Vadakkepat, C.F. Starmer, Smartphone spectrophotometer for point-of-care diagnostics in low-resource settings, in: *Humanitarian Technology Conference (R10-HTC), 2015 IEEE Region 10* (pp. 1-6).
- [74] H.J.S. de Oliveira, P.L. de Almeida Jr, B.A. Sampaio, J.P.A. Fernandes, O.D. Pessoa-Neto, E.A. de Lima, L.F. de Almeida, A handheld smartphone-controlled spectrophotometer based on hue to wavelength conversion for molecular absorption and emission measurements, *Sensors and Actuators B: Chemical*, 238 (2017) 1084-1091.
- [75] K.D. Long, H. Yu, B.T. Cunningham, Smartphone instrument for portable enzyme-linked immunosorbent assays, *Biomedical optics express*, 5 (11) (2014) 3792-3806.

- [76] D. Gallegos, K.D. Long, H. Yu, P.P. Clark, Y. Lin, S. George, P. Nath, B.T. Cunningham, Label-free biodetection using a smartphone, *Lab on a Chip*, 13 (11) (2013) 2124-2132.
- [77] H. Yu, Y. Tan, B.T. Cunningham, Smartphone fluorescence spectroscopy, *Analytical chemistry*, 86 (17) (2014) 8805-8813.
- [78] R. Grigorova, J.R. Norris, *Methods in microbiology*, Volume 22: Techniques in Microbial Ecology.
- [79] C. Zhang, W.B. Chen, An effective and robust method for automatic bacterial colony enumeration, in: *International Conference on Semantic Computing, 2007. ICSC 2007* (pp. 581-588).
- [80] J.L. Minoi, T.T. Chiang, T. Lim, Z. Yusoff, A.H.A. Karim, A. Zuharnain, Mobile vision-based automatic counting of bacteria colonies, in: *International Conference on Information and Communication Technology (ICICTM)* (pp. 41-46).
- [81] J. Austerjost, D. Marquard, L. Raddatz, D. Geier, T. Becker, T. Scheper, P. Lindner, S. Beutel, A smart device application for the automated determination of E. coli colonies on agar plates, *Engineering in Life Sciences* 17 (2017) 959-966.
- [82] M. Poladia, P. Fakatkar, S. Hatture, S.S. Rathod, S. Kuruwa, Detection and analysis of waterborne bacterial colonies using image processing and smartphones, in: *International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), 2015* (pp. 159-164).
- [83] S. Kumar, R.V.R. Choudhury, S. Laxman, *Colonizer: An android OS based automated microbial colony counter* (No. e2792v1) (2017) PeerJ Preprints.
- [84] Y. Liu, J. Zhang, M. Richards, B. Pham, P. Roe, A. Clarke, Towards continuous surveillance of fruit flies using sensor networks and machine vision, in: *5th International Conference on Wireless Communications, Networking and Mobile Computing, 2009. WiCom'09* (pp. 1-5).

- [85] K. Aizawa, K. Maeda, M. Ogawa, Y. Sato, M. Kasamatsu, K. Waki, H. Takimoto, Comparative study of the routine daily usability of foodlog: A smartphone-based food recording tool assisted by image retrieval, *Journal of diabetes science and technology*, 8 (2) (2014) 203-208.
- [86] W. Zhang, Q. Yu, B. Siddiquie, A. Divakaran, H. Sawhney, “Snap-n-Eat” Food Recognition and Nutrition Estimation on a Smartphone, *Journal of diabetes science and technology*, 9 (3) (2015) 525-533.
- [87] R. Zaman, C.H. Cho, K. Hartmann-Vaccarezza, T.N. Phan, G. Yoon, J.W. Chong, Novel fingertip image-based heart rate detection methods for a smartphone, *Sensors*, 17 (2) (2017) 358.
- [88] D.N. Breslauer, R.N. Maamari, N.A. Switz, W.A. Lam, D.A. Fletcher, Mobile phone based clinical microscopy for global health applications, *PloS one*, 4 (7) (2009) e6320.
- [89] S.A. Lee, C. Yang, A smartphone-based chip-scale microscope using ambient illumination, *Lab on a Chip*, 14 (16) (2014) 3056-3063.
- [90] E.C. Larson, M. Goel, G. Boriello, S. Heltshe, M. Rosenfeld, S.N. Patel, SpiroSmart: using a microphone to measure lung function on a mobile phone, in: *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 280-289).
- [91] E.C. Larson, M. Goel, M. Redfield, G. Boriello, M. Rosenfeld, S.N. Patel, Tracking lung function on any phone, In: *Proceedings of the 3rd ACM Symposium on Computing for Development* (p. 29).
- [92] E.C. Larson, T. Lee, S. Liu, M. Rosenfeld, S.N. Patel, Accurate and privacy preserving cough sensing using a low-cost microphone, in: *Proceedings of the 13th international conference on Ubiquitous computing* (pp. 375-384).
- [93] Y. Nam, B.A. Reyes, K.H. Chon, Estimation of respiratory rates using the built-in microphone of a smartphone or headset, *IEEE Journal of Biomedical and Health Informatics*, 20 (6) (2016) 1493-1501.
- [94] N.C. Chen, K.C. Wang, H.H. Chu, Listen-to-nose: a low-cost system to record nasal symptoms in daily life, in: *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 590-591).

- [95] H. Nakano, K. Hirayama, Y. Sadamitsu, A. Toshimitsu, H. Fujita, S. Shin, T. Tanigawa, Monitoring sound to quantify snoring and sleep apnea severity using a smartphone: proof of concept, *Journal of Clinical Sleep Medicine*, 10 (1) (2014) 73-78.
- [96] Y. Na, H.S. Joo, H. Yang, S. Kang, S.H. Hong, J. Woo, Smartphone-based hearing screening in noisy environments, *Sensors*, 14 (6) (2014) 10346-10360.
- [97] D.W. Swanepoel, H.C. Myburgh, D.M. Howe, F. Mahomed, R.H. Eikelboom, Smartphone hearing screening with integrated quality control and data management, *International Journal of Audiology*, 53 (12) (2014) 841-849.
- [98] W. Wang, L. Xie, X. Wang, Tremor detection using smartphone-based acoustic sensing, in: *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*, (2017) 309-312.
- [99] J.E. Siegel, R. Bhattacharyya, S. Kumar, S.E. Sarma, Air filter particulate loading detection using smartphone audio and optimized ensemble classification, *Engineering Applications of Artificial Intelligence*, 66 (2017) 104-112.
- [100] S. Li, X. Fan, Y. Zhang, W. Trappe, J. Lindqvist, R.E. Howard, Auto++: Detecting Cars Using Embedded Microphones in Real-Time, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1 (3) (2017) 70:1-70:20.
- [101] C.L. Petersen, T.P. Chen, J.M. Ansermino, G.A. Dumont, Design and evaluation of a low-cost smartphone pulse oximeter, *Sensors*, 13 (12) (2013) 16882-16893.
- [102] J. Broeders, D. Croux, M. Peeters, T. Beyens, S. Duchateau, T.J. Cleij, P. Wagner, R. Thoelen, W. De Ceuninck, Mobile application for impedance-based biomimetic sensor readout, *IEEE Sensors Journal*, 13 (7) (2013) 2659-2665.
- [103] U. Blanke, G. Troster, T. Franke, P. Lukowicz, Capturing crowd dynamics at large scale events using participatory gps-localization, in: *2014 IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)* (pp. 1-7).

- [104] M. Wirz, T. Franke, D. Roggen, E. Mittleton-Kelly, P. Lukowicz, G. Tröster, Probing crowd density through smartphones in city-scale mass gatherings, *EPJ Data Science*, 2 (1) (2013) 5.
- [105] B. Charlton, J. Hood, E. Sall, M.A. Schwartz, *Bicycle route choice data collection using GPS-enabled smartphones* (2011) (No. 11-2652).
- [106] J. Whipple, W. Arensman, M.S. Boler, A public safety application of GPS-enabled smartphones and the android operating system, in: *IEEE International Conference on Systems, Man and Cybernetics, 2009* (pp. 2059-2061).
- [107] J.J. Guiry, P. van de Ven, J. Nelson, L. Warmerdam, H. Riper, Activity recognition with smartphone support, *Medical engineering and physics*, 36 (6) (2014) 670-675.
- [108] G. Bieber, P. Koldrack, C. Sablowski, C. Peter, B. Urban, Mobile physical activity recognition of stand-up and sit-down transitions for user behavior analysis, in: *Proceedings of the 3rd International Conference on Pervasive Technologies Related to Assistive Environments* (2010) (p. 50).
- [109] A. Bayat, M. Pomplun, D.A. Tran, A study on human activity recognition using accelerometer data from smartphones, *Procedia Computer Science*, 34 (2014) 450-457.
- [110] Y. Kwon, K. Kang, C. Bae, Unsupervised learning for human activity recognition using smartphone sensors, *Expert Systems with Applications*, 41 (14) (2014) 6067-6074.
- [111] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J. Havinga, Fusion of smartphone motion sensors for physical activity recognition, *Sensors*, 14 (6) (2014) 10146-10176.
- [112] A. Ghosh, G. Riccardi, Recognizing human activities from smartphone sensor signals, in: *Proceedings of the 22nd ACM international conference on Multimedia* (2014) (pp. 865-868).
- [113] M.A. Habib, M.S. Mohktar, S.B. Kamaruzzaman, K.S. Lim, T.M. Pin, F. Ibrahim, Smartphone-based solutions for fall detection and prevention: challenges and open issues, *Sensors*, 14 (4) (2014) 7181-7208.

- [114] C. Tacconi, S. Mellone, L. Chiari, Smartphone-based applications for investigating falls and mobility, in: *5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2011* (pp. 258-261).
- [115] Z. Zhao, Y. Chen, S. Wang, Z. Chen, Fallalarm: Smart phone based fall detecting and positioning system, *Procedia Computer Science*, 10 (2012) 617-624.
- [116] Y. He, Y. Li, S.D. Bao, Fall detection by built-in tri-accelerometer of smartphone, in: *IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), 2012* (pp. 184-187).
- [117] R.J. Dzung, Y.C. Fang, I.C. Chen, A feasibility study of using smartphone built-in accelerometers to detect fall portents, *Automation in Construction*, 38 (2014) 74-86.
- [118] S. Dashti, J.D. Bray, J. Reilly, S. Glaser, A. Bayen, E. Mari, Evaluating the reliability of phones as seismic monitoring instruments, *Earthquake Spectra*, 30 (2) (2014) 721-742.
- [119] J. Reilly, S. Dashti, M. Ervasti, J.D. Bray, S.D. Glaser, A.M. Bayen, Mobile phones as seismologic sensors: automating data extraction for the iShake system, *IEEE Transactions on Automation Science and Engineering*, 10 (2) (2013) 242-251.
- [120] Q. Kong, R.M. Allen, M.D. Kohler, T.H. Heaton, J. Bunn, Structural health monitoring of buildings using smartphone sensors, *Seismological Research Letters*, 89 (2A) (2018) 594-602.
- [121] M. Feng, Y. Fukuda, M. Mizuta, E. Ozer, Citizen sensors for SHM: use of accelerometer data from smartphones, *Sensors*, 15 (2015) 2980-2998.
- [122] Y. Yu, R. Han, X. Zhao, X. Mao, W. Hu, D. Jiao, M. Li, J. Ou, Initial validation of mobile-structural health monitoring method using smartphones, *International Journal of Distributed Sensor Networks*, article ID 274391 (2015).
- [123] Y. Li, F. Xue, L. Feng, Z. Qu, A driving behavior detection system based on smartphone's built-in sensor, *International Journal of Communication Systems*, 30 (2017) 1-13.
- [124] F. Li, H. Zhang, H. Che, X. Qiu, Dangerous driving behavior detection using smartphone sensors, *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, (2016) 1902-1907.

- [125] J. Yu, Z. Chen, Y. Zhu, Y. Chen, L. Kong, M. Li, Fine-grained abnormal driving behaviors detection and identification with smartphones, *IEEE Transactions on Mobile Computing*, In Press.
- [126] A.A. Tecimer, Z.C. Taysi, A.G. Yavuz, M.E. Karşlıgil Yavuz, Assessment of vehicular transportation quality via smartphones, *Turkish Journal of Electrical Engineering & Computer Sciences*, 23 (2015) 2161-2170.
- [127] D.A. Johnson, M.M. Trivedi, Driving style recognition using a smartphone as a sensor platform, in: *14th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2011* (pp. 1609-1615).
- [128] R. Bhoraskar, N. Vankadhara, B. Raman, P. Kulkarni, Wolverine: Traffic and road condition estimation using smartphone sensors, in: *Fourth International Conference on Communication Systems and Networks (COMSNETS), 2012* (pp. 1-6).
- [129] A. Allouch, A. Koubâa, T. Abbes, A. Ammar, RoadSense: Smartphone Application to Estimate Road Conditions Using Accelerometer and Gyroscope, *IEEE Sensors Journal*, 17 (13) (2017) 4231-4238.
- [130] F. Seraj, B.J. van der Zwaag, A. Dilo, T. Luarasi, P. Havinga, RoADS: a road pavement monitoring system for anomaly detection using smart phones, *Big Data Analytics in the Social and Ubiquitous Context*, Springer (2014) 128-146.
- [131] Z. Lin, D. Meng, Q. Zhong, Design and implementation of OTG communication system terminal based on USB, in: *International Conference on Control, Automation and Systems Engineering (CASE), 2011* (pp. 1-4).
- [132] T. Le, H.D. Han, T.H. Hoang, V.C. Nguyen, C.K. Nguyen, A low cost mobile ECG monitoring device using two active dry electrodes, in: *IEEE Sixth International Conference on Communications and Electronics (ICCE), 2016* (pp. 271-276).
- [133] S. Ghosh, K. Aggarwal, C.H. Ahn, A new mobile healthcare system using smartphone and lab-on-a-chip for on-site diagnostics of malaria, *21st International Conference on Miniaturized Systems for Chemistry and Life Sciences (MicroTAS), 2017* (pp. 1-2).

- [134] Y. Dou, Z. Jiang, W. Deng, J. Su, S. Chen, H. Song, A. Aldalbahi, X. Zuo, S. Song, J. Shi, C. Fan, Portable detection of clenbuterol using a smartphone-based electrochemical biosensor with electric field-driven acceleration, *Journal of Electroanalytical Chemistry*, 781 (2016) 339-344.
- [135] W. Deng, Y. Dou, P. Song, H. Xu, A. Aldalbahi, N. Chen, N. Nasser El-Sayed, J. Gao, J. Lu, S. Song, X. Zuo, Lab on smartphone with interfaced electrochemical chips for on-site gender verification, *Journal of Electroanalytical Chemistry*, 777 (2016) 117-122.
- [136] N.M. Rodrigues, L.S. Rosado, P.M. Ramos, A portable embedded contactless system for the measurement of metallic material conductivity and lift-off, *Measurement*, 111 (2017) 441-450.
- [137] J. Aymerich, A. Marquez, L. Teres, X. Munoz-Berbel, C. Jimenez, C. Dominguez, F. Serra-Graells, M. Dei, Cost-effective smartphone-based reconfigurable electrochemical instrument for alcohol determination in whole blood samples, *Biosensors and Bioelectronics*, 117 (2018) 736-742.
- [138] E.H. Doeven, G.J. Barbante, A.J. Harsant, P.S. Donnelly, T.U. Connell, C.F. Hogan, P.S. Francis, Mobile phone-based electrochemiluminescence sensing exploiting the 'USB On-The-Go' protocol, *Sensors and Actuators B: Chemical*, 216 (2015) 608-613.
- [139] S. Li, D. Zhang, J. Liu, C. Cheng, L. Zhu, C. Li, Y. Lu, S.S. Low, B. Su, Q. Liu, Electrochemiluminescence on smartphone with silica nanopores membrane modified electrodes for nitroaromatic explosives detection, *Biosensors and Bioelectronics*, article in press (2018).
- [140] I. Hussain, K. Ahamad, P. Nath, Water turbidity sensing using a smartphone, *RSC Advances*, 6 (27) (2016) 22374-22382.
- [141] I. Hussain, A.J. Bora, D. Sarma, K.U. Ahamad, P. Nath, Design of a smartphone platform compact optical system operational both in visible and near infrared spectral regime, *IEEE Sensors Journal*, 18 (12) (2018) 4933-4939.
- [142] T. Das, D. Hatiboruah, N. Chamuah, I. Hussain, U. Bora, P. Nath, Accurate estimation of mercury level concentration in water using smartphone, *Optical Sensing and Detection V*, vol. 10680 (2018).

- [143] I. Hussain, K.U. Ahamad, P. Nath, Low-cost, robust and field portable smartphone platform photometric sensor for fluoride level detection in drinking water, *Analytical Chemistry*, 89 (2017) 767-775.
- [144] I. Hussain, M. Das, K.U. Ahamad, P. Nath, Water salinity detection using a smartphone, *Sensors and Actuators B: Chemical*, 239 (2017) 1042-1050.
- [145] I. Veen, A.Y. Majid, P. Pawelczak, OTGS: reducing energy consumption of USB-connected low-cost sensors on smartphones, in: *Proceedings of the IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*.
- [146] C. Yao, A. Sun, D.A. Hall, Efficient power harvesting from the mobile phone audio jack for mHealth peripherals, in: *IEEE Global Humanitarian Technology Conference (GHTC), 2015* (pp. 219-225).
- [147] A. Sun, T. Wambach, A.G. Venkatesh, D.A. Hall, A low-cost smartphone-based electrochemical biosensor for point-of-care diagnostics, in: *IEEE Biomedical Circuits and Systems Conference (BioCAS), 2014* (pp. 312-315).
- [148] A. Sun, T. Phelps, C. Yao, A.G. Venkatesh, D. Conrad, D.A. Hall, Smartphone-Based pH Sensor for Home Monitoring of Pulmonary Exacerbations in Cystic Fibrosis, *Sensors*, 17 (6) (2017) 1245.
- [149] E. Aronoff-Spencer, A.G. Venkatesh, A. Sun, H. Brickner, D. Looney, D.A. Hall, Detection of Hepatitis C core antibody by dual-affinity yeast chimera and smartphone-based electrochemical sensing, *Biosensors and Bioelectronics*, 86 (2016) 690-696.
- [150] X. Wang, M.R. Gartia, J. Jiang, T.W. Chang, J. Qian, Y. Liu, X. Liu, G.L. Liu, Audio jack based miniaturized mobile phone electrochemical sensing platform, *Sensors and Actuators B: Chemical*, 209 (2015) 677-685.
- [151] T. Fujimoto, S. Kawahara, Y. Fuchigami, S. Shimokawa, Y. Nakamura, K. Fukayama, M. Kamahori, S. Uno, Portable Electrochemical Sensing System Attached to Smartphones and Its

Incorporation with Paper-based Electrochemical Glucose Sensor, *International Journal of Electrical and Computer Engineering (IJECE)*, 7 (3) (2017) 1423-1429.

[152] A. Nemiroski, D.C. Christodouleas, J.W. Hennek, A.A. Kumar, E.J. Maxwell, M.T. Fernández-Abedul, G.M. Whitesides, Universal mobile electrochemical detector designed for use in resource-limited applications, *Proceedings of the National Academy of Sciences*, 111 (33) (2014) 11984-11989.

[153] H. Jiang, A. Sun, A.G. Venkatesh, D.A. Hall, An audio jack-based electrochemical impedance spectroscopy sensor for point-of-care diagnostics, *IEEE Sensors Journal*, 17 (3) (2017) 589-597.

[154] A. Dinh, Heart activity monitoring on smartphone, in: *International Conference on Biomedical Engineering and Technology* (2011) (Vol. 11, pp. 45-49).

[155] J.J. Oresko, Z. Jin, J. Cheng, S. Huang, Y. Sun, H. Duschl, A.C. Cheng, A wearable smartphone-based platform for real-time cardiovascular disease detection via electrocardiogram processing, *IEEE Transactions on Information Technology in Biomedicine*, 14 (3) (2010) 734-740.

[156] Z.M. Lin, C.H. Chang, N.K. Chou, Y.H. Lin, Bluetooth Low Energy (BLE) based blood pressure monitoring system, in: *International Conference on Intelligent Green Building and Smart Grid (IGBSG), 2014* (pp. 1-4).

[157] P. Keith-Hynes, B. Mize, A. Robert, J. Place, The Diabetes Assistant: a smartphone-based system for real-time control of blood glucose, *Electronics*, 3 (4) (2014) 609-623.

[158] G. Cappon, G. Acciaroli, M. Vettoretti, A. Facchinetti, G. Sparacino, Wearable Continuous Glucose Monitoring Sensors: A Revolution in Diabetes Treatment, *Electronics*, 6 (3) (2017) 65.

[159] O. Postolache, P.S. Girão, M. Ribeiro, M. Guerra, J. Pincho, F. Santiago, A. Pena, Enabling telecare assessment with pervasive sensing and Android OS smartphone, in: *IEEE International Workshop on Medical Measurements and Applications Proceedings (MeMeA), 2011* (pp. 288-293).

[160] F. Bianchi, S.J. Redmond, M.R. Narayanan, S. Cerutti, B.G. Celler, N.H. Lovell, Falls event detection using triaxial accelerometry and barometric pressure measurement, in: *Annual*

- International Conference of the IEEE Engineering in Medicine and Biology Society. EMBC 2009* (pp. 6111-6114).
- [161] P. Zappi, E. Bales, J.H. Park, W. Griswold, T.Š. Rosing, The citisense air quality monitoring mobile sensor node, in: *Proceedings of the 11th ACM/IEEE Conference on Information Processing in Sensor Networks, 2012 Beijing, China*.
- [162] Y. Jiang, K. Li, L. Tian, R. Piedrahita, X. Yun, O. Mansata, Q. Lv, R.P. Dick, M. Hannigan, L. Shang, Maqs: A mobile sensing system for indoor air quality, in: *Proceedings of the 13th international conference on Ubiquitous computing* (2011) (pp. 493-494).
- [163] J. Potts, S. Sukittanon, Exploiting Bluetooth on Android mobile devices for home security application, in: *Proceedings of IEEE Southeastcon, 2012* (pp. 1-4).
- [164] T. Rahman, A.T. Adams, M. Zhang, E. Cherry, B. Zhou, H. Peng, T. Choudhury, BodyBeat: a mobile system for sensing non-speech body sounds, in: *MobiSys* (2014) (Vol. 14, pp. 2-13).
- [165] G.F. Giordano, M.B. Vicentini, R.C. Murer, F. Augusto, M.F. Ferrão, G.A. Helfer, A.B. da Costa, A.L. Gobbi, L.W. Hantao, R.S. Lima, Point-of-use electroanalytical platform based on homemade potentiostat and smartphone for multivariate data processing, *Electrochimica Acta*, 219 (2016) 170-177.
- [166] J. Jiang, X. Wang, R. Chao, Y. Ren, C. Hu, Z. Xu, G.L. Liu, Smartphone based portable bacteria pre-concentrating microfluidic sensor and impedance sensing system, *Sensors and Actuators B: Chemical*, 193 (2014) 653-659.
- [167] M. Grossi, B. Riccò, Electrical impedance spectroscopy (EIS) for biological analysis and food characterization: a review, *Journal of Sensors and Sensor Systems*, 6 (2017) 303-325.
- [168] D. Zhang, J. Jiang, J. Chen, Q. Zhang, Y. Lu, Y. Yao, S. Li, G.L. Liu, Q. Liu, Smartphone-based portable biosensing system using impedance measurement with printed electrodes for 2, 4, 6-trinitrotoluene (TNT) detection, *Biosensors and Bioelectronics*, 70 (2015) 81-88.

- [169] D. Zhang, Y. Lu, Q. Zhang, L. Liu, S. Li, Y. Yao, J. Jiang, G.L. Liu, Q. Liu, Protein detecting with smartphone-controlled electrochemical impedance spectroscopy for point-of-care applications, *Sensors and Actuators B: Chemical*, 222 (2016) 994-1002.
- [170] A. Choi, J.Y. Kim, S. Jo, J.H. Jee, S.B. Heymsfield, Y.A. Bhagat, I. Kim, J. Cho, Smartphone-based bioelectrical impedance analysis devices for daily obesity management, *Sensors*, 15 (9) (2015) 22151-22166.
- [171] A.J. Das, A. Wahi, I. Kothari, R. Raskar, Ultra-portable, wireless smartphone spectrometer for rapid, non-destructive testing of fruit ripeness, *Scientific reports*, 6 (2016) 32504.
- [172] A. Das, T. Swedish, A. Wahi, M. Moufarrej, M. Noland, T. Gurry, E. Aranda-Michel, D. Aksel, S. Wagh, V. Sadashivaiah, X. Zhang, R. Raskar, Mobile phone based mini-spectrometer for rapid screening of skin cancer, in: *Next-Generation Spectroscopic Technologies Viii* (2015) (Vol. 9482, p. 94820M). International Society for Optics and Photonics.
- [173] R. Want, Near field communication, *IEEE Pervasive Computing*, 10 (3) (2011) 4-7.
- [174] H. Du, NFC technology: Today and tomorrow, *International Journal of Future Computer and Communication*, 2 (4) (2013) 351-354.
- [175] N. Leavitt, Are mobile payments ready to cash in yet? *Computer*, 45 (9) (2012) 15-18.
- [176] Y.Y. Chen, M.L. Tsai, F.J. Chang, The design of secure mobile coupon mechanism with the implementation for NFC smartphones, *Computers & Electrical Engineering*, 59 (2017) 204-217.
- [177] M. Aigner, S. Dominikus, M. Feldhofer, A system of secure virtual coupons using NFC technology, in: *Fifth Annual IEEE International Conference on Pervasive Computing and Communications Workshops, 2007* (pp. 362-366).
- [178] J. Pesonen, E. Horster, Near field communication technology in tourism, *Tourism Management Perspectives*, 4 (2012) 11-18.
- [179] H. Mika, H. Mikko, Y.O. Arto, Practical implementations of passive and semi-passive nfc enabled sensors, in: *First International Workshop on Near Field Communication, 2009* (pp. 69-74).

- [180] G. Alfian, J. Rhee, H. Ahn, J. Lee, U. Farooq, M.F. Ijaz, M.A. Syaekhoni, Integration of RFID, wireless sensor networks, and data mining in an e-pedigree food traceability system, *Journal of Food Engineering*, 212 (2017) 65-75.
- [181] P. Kassal, I.M. Steinberg, M.D. Steinberg, Wireless smart tag with potentiometric input for ultra low-power chemical sensing, *Sensors and actuators B: chemical*, 184 (2013) 254-259.
- [182] M.D. Steinberg, P. Kassal, I. Kereković, I.M. Steinberg, A wireless potentiostat for mobile chemical sensing and biosensing, *Talanta*, 143 (2015) 178-183.
- [183] P. Kassal, J. Kim, R. Kumar, W.R. de Araujo, I.M. Steinberg, M.D. Steinberg, J. Wang, Smart bandage with wireless connectivity for uric acid biosensing as an indicator of wound status, *Electrochemistry Communications*, 56 (2015) 6-10.
- [184] P. Kassal, M.D. Steinberg, E. Horak, I.M. Steinberg, Wireless fluorimeter for mobile and low cost chemical sensing: a paper based chloride assay, *Sensors and Actuators B: Chemical*, 275 (2018) 230-236.
- [185] M. Magno, D. Brunelli, L. Sigrist, R. Andri, L. Cavigelli, A. Gomez, L. Benini, InfiniTime: Multi-sensor wearable bracelet with human body harvesting, *Sustainable Computing: Informatics and Systems*, 11 (2016) 38-49.
- [186] M.A. Carvajal, P. Escobedo, M. Jiménez-Melguizo, M.S. Martínez-García, F. Martínez-Martí, A. Martínez-Olmos, A.J. Palma, A compact dosimetric system for MOSFETs based on passive NFC tag and smartphone, *Sensors and Actuators A: Physical*, 267 (2017) 82-89.
- [187] D.P. Rose, M.E. Ratterman, D.K. Griffin, L. Hou, N. Kelley-Loughnane, R.R. Naik, J.A. Hagen, I. Papautsky, J.C. Heikenfeld, Adhesive RFID sensor patch for monitoring of sweat electrolytes, *IEEE Transactions on Biomedical Engineering*, 62 (6) (2015) 1457-1465.
- [188] C. Matoschitz, R. Lurf, M. Meindl, M. Bammer, NFC Based Smart Biosensor—An Introduction to Battery-less Enzymatic Amperometric Glucose Sensor Based on NFC Technology, *Journal of Instrumentation*, 3 (08) (2008) S08004.

- [189] M. Boada, A. Lázaro, R. Villarino, D. Girbau, Battery-Less Soil Moisture Measurement System Based on a NFC Device With Energy Harvesting Capability, *IEEE Sensors Journal*, 18 (13) (2018) 5541-5549.
- [190] G. Xu, Q. Zhang, Y. Lu, L. Liu, D. Ji, S. Li, Q. Liu, Passive and wireless near field communication tag sensors for biochemical sensing with smartphone, *Sensors and Actuators B: Chemical*, 246 (2017) 748-755.
- [191] J.M. Azzarelli, K.A. Mirica, J.B. Ravensbæk, T.M. Swager, Wireless gas detection with a smartphone via rf communication, *Proceedings of the National Academy of Sciences*, 111 (51) (2014) 18162-18166.
- [192] Z. Ma, P. Chen, W. Cheng, K. Yan, L. Pan, Y. Shi, G. Yu, Highly sensitive, printable nanostructured conductive polymer wireless sensor for food spoilage detection, *Nano Letters*, 18 (7) (2018) 4570-4575.
- [193] W. Zamora, C.T. Calafate, J.C. Cano, P. Manzoni, A survey of smartphone-based crowdsensing solutions, *Mobile Information Systems*, ID 9681842 (2016).
- [194] N.D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, A.T. Campbell, A survey of mobile phone sensing, *IEEE Communications Magazine*, September (2010).
- [195] C. Leonardi, B. Lepri, A. Cappellotto, F. Antonelli, M. Caraviello, SecondNose: an air quality mobile crowdsensing system, *Proceedings of the 8th Nordic Conference on Human-Computer Interaction: Fun, Fast, Foundational*, (2014) 1051-1054.
- [196] V. Radu, L. Kriara, M.K. Marina, Pazl: a mobile crowdsensing based indoor WiFi monitoring system, *9th International Conference on Network and Service Management (CNSM)*, (2013) 75-83.
- [197] X. Hu, T.H.S. Chu, H.C.B. Chan, V.C.M. Leung, Vita: a crowdsensing-oriented mobile cyber-physical system, *IEEE Transactions on Emerging Topics in Computing*, 1 (1) (2013) 148-165.

- [198] M.R. Ra, B. Liu, T. La Porta, R. Govindan, Medusa: a programming framework for crowd-sensing applications, *Proceedings of the 10th International Conference on Mobile Systems, Applications and Services*, (2012) 337-350.
- [199] N.D. Lane, M. Lin, M. Mohammad, X. Yang, H. Lu, G. Cardone, S. Ali, A. Doryab, E. Berke, A.T. Campbell, T. Choudhury, BeWeel: sensing sleep, physical activities and social interactions to promote wellbeing, *Mobile Networks and Applications*, 19 (3) (2014) 345-359.
- [200] A. Kadomura, H.H. Chu, K.C.Y. Li, K. Tsukada, A.Y.C. Chen, I. Siiio, Sensing fork and persuasive game for improving eating behavior, *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication*, (2013) 71-74.
- [201] A. Dickinson, P. Egglestone, M. Lochrie, UKKO: enriching persuasive location based games with environmental sensor data, *Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play*, (2015) 493-498.
- [202] R. Gravina, P. Alinia, H. Ghasemzadeh, G. Fortino, Multi-sensor fusion in body sensor networks: state-of-the-art and research challenges, *Information Fusion*, 35 (2017) 68-80.
- [203] S. Kanarachos, S.R.G. Christopoulos, A. Chroneos, Smartphones as an integrated platform for monitoring driver behavior: the role of sensor fusion and connectivity, *Transportation Research Part C*, 95 (2018) 867-882.
- [204] C. Zhang, P. Patras, H. Haddadi, Deep learning in mobile and wireless networking: a survey, *IEEE Communications Surveys & Tutorials*, (2018) arXiv preprint arXiv:1803.04311.
- [205] A. Shrestha, M. Won, Deepwalking: enabling smartphone-based walking speed estimation using deep learning, (2018) arXiv preprint arXiv:1805.03368.
- [206] R. Perez-Torres, C. Torres-Huitzil, H. Galeana-Zapien, Power management techniques in smartphone-based mobility sensing systems: a survey, *Pervasive and Mobile Computing*, 31 (2016) 1-21.

- [207] K.L.M. Ang, J.K.P. Seng, A.M. Zungeru, Optimizing energy consumption for big data collection in large-scale wireless sensor networks with mobile collectors, *IEEE Systems Journal*, 12 (1) (2018) 616-626.
- [208] J. Wang, Y. Wang, D. Zhang, S. Helal, Energy saving techniques in mobile crowd sensing: current state and future opportunities, *IEEE Communications Magazine*, May (2018) 2-8.
- [209] N. Jain, X. Fan, W.D. Leon-Salas, A.M. Lucietto, Extending battery life of smartphones by overcoming idle power consumption using ambient light energy harvesting, *IEEE International Conference on Industrial Technology (ICIT)*, (2018) 978-983.
- [210] Y. Dai, T. Li, B. Liu, M. Song, H. Chen, Exploiting dynamic thermal energy harvesting for reusing in smartphone with mobile applications, *Proceedings of the Twenty-Third International Conference on Architectural Support for Programming Languages and Operating Systems*, (2018) 243-256.
- [211] Y. Liang, Z. Cai, J. Yu, Q. Han, Y. Li, Deep learning based inference of private information using embedded sensors in smart devices, *IEEE Network*, 32 (4) (2018) 8-14.
- [212] D. Wu, S. Si, S. Wu, R. Wang, Dynamic trust relationships aware data privacy protection in mobile crowd-sensing, *IEEE Internet of Things Journal*, 5 (4) (2018) 2958-2970.
- [213] T. Dimitriou, Privacy-respecting reward generation and accumulation for participatory sensing applications, *Pervasive and Mobile Computing*, 49 (2018) 139-152.
- [214] H. Jin, L. Su, H. Xiao, K. Nahrstedt, Incentive mechanism for privacy-aware data aggregation in mobile crowd sensing systems, *IEEE ACM Transactions on Networking*, 99 (2018) 1-14.

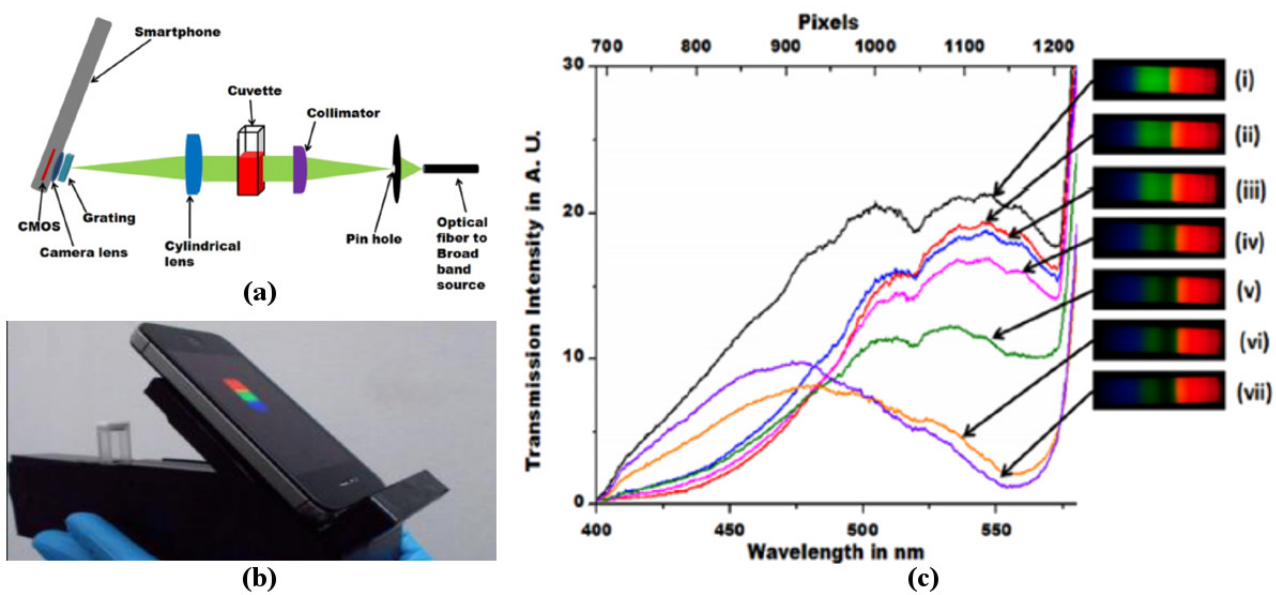


Fig. 1 Optical spectrophotometer for mobile phone. Reprinted with permission from [69].

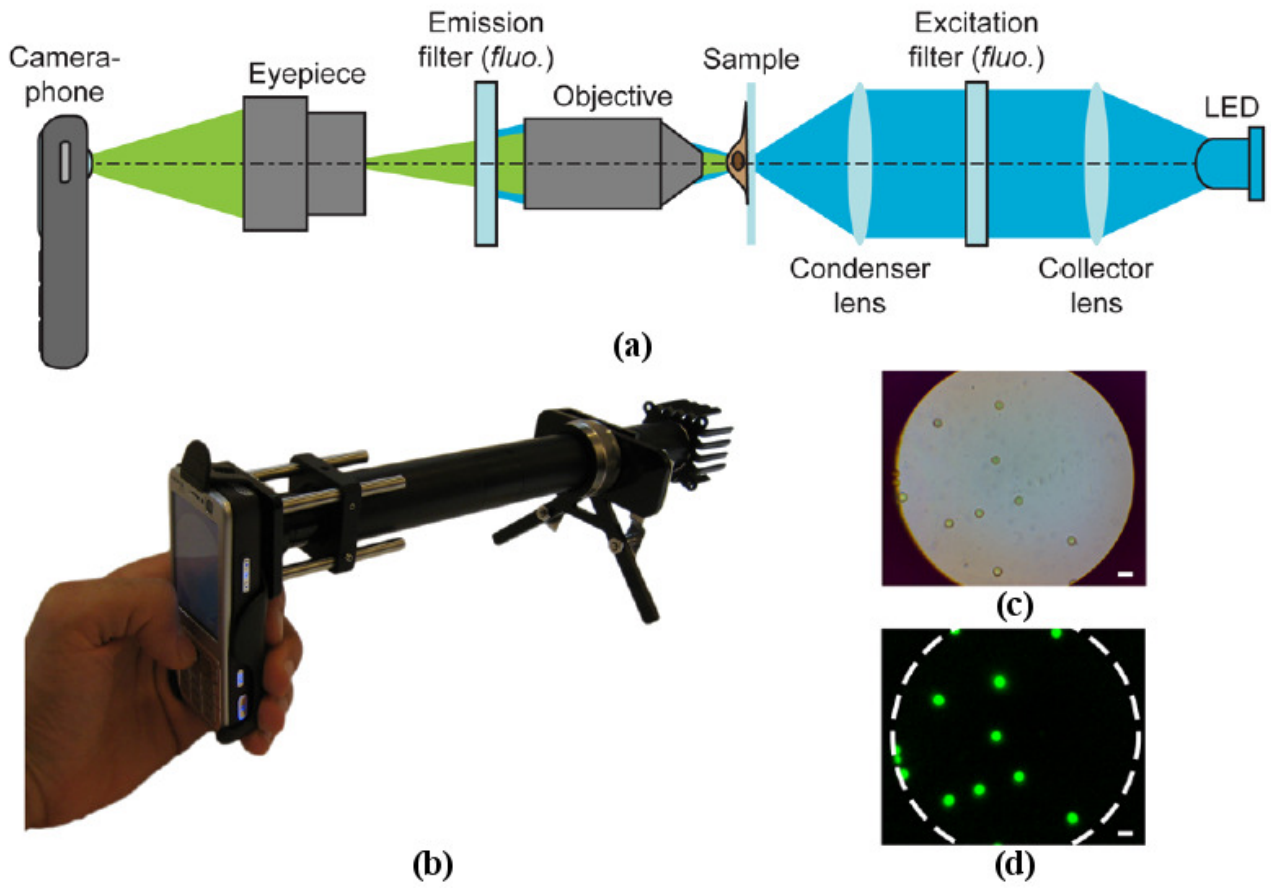


Fig. 2 Smartphone based fluorescence microscopy for point-of-care testing. Reprinted with permission from [88].

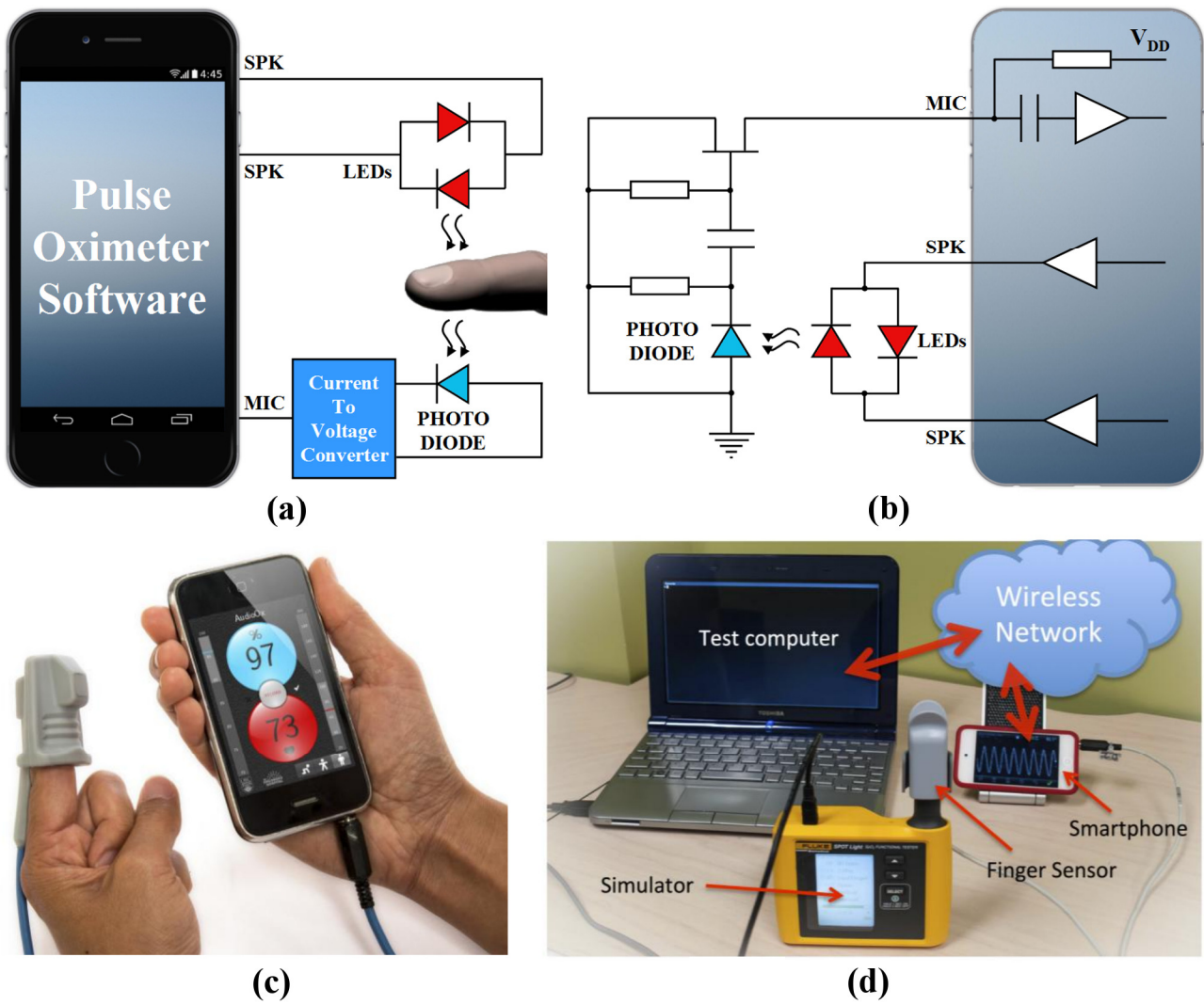


Fig. 3 Pulse oximeter for the measurements of oxygen saturation and heart rate exploiting the smartphone audio port. Reprinted with permission from [101].

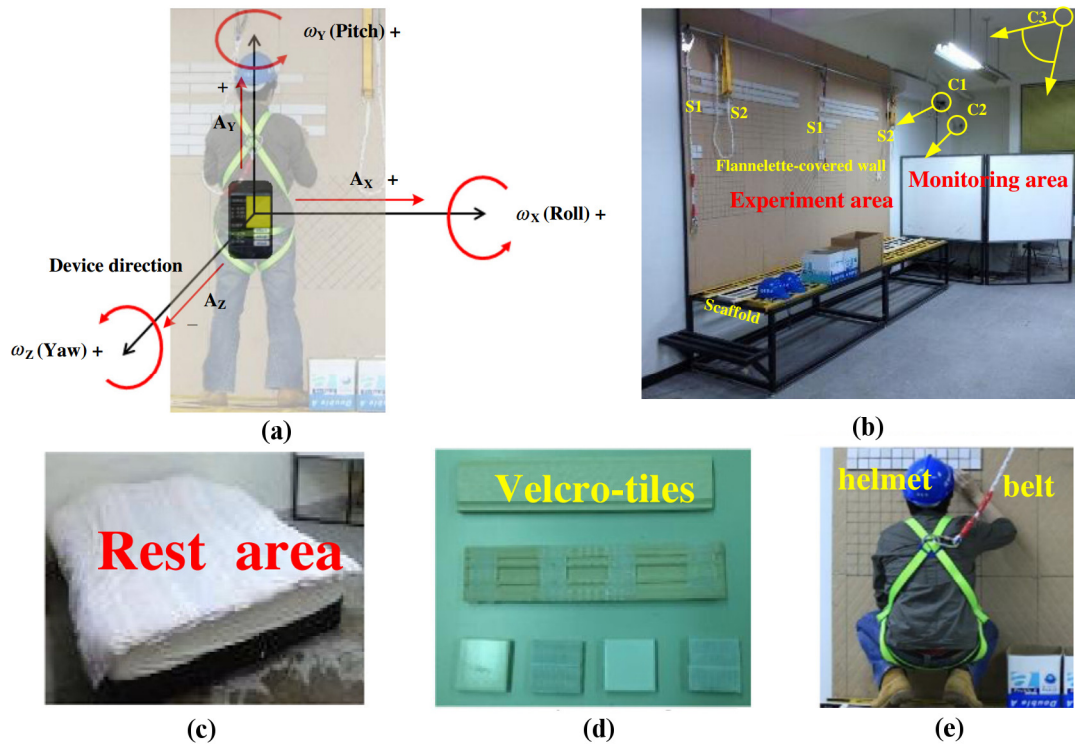


Fig. 4 Smartphone based system to prevent fall accidents in the construction industry. Reprinted with permission from [117].

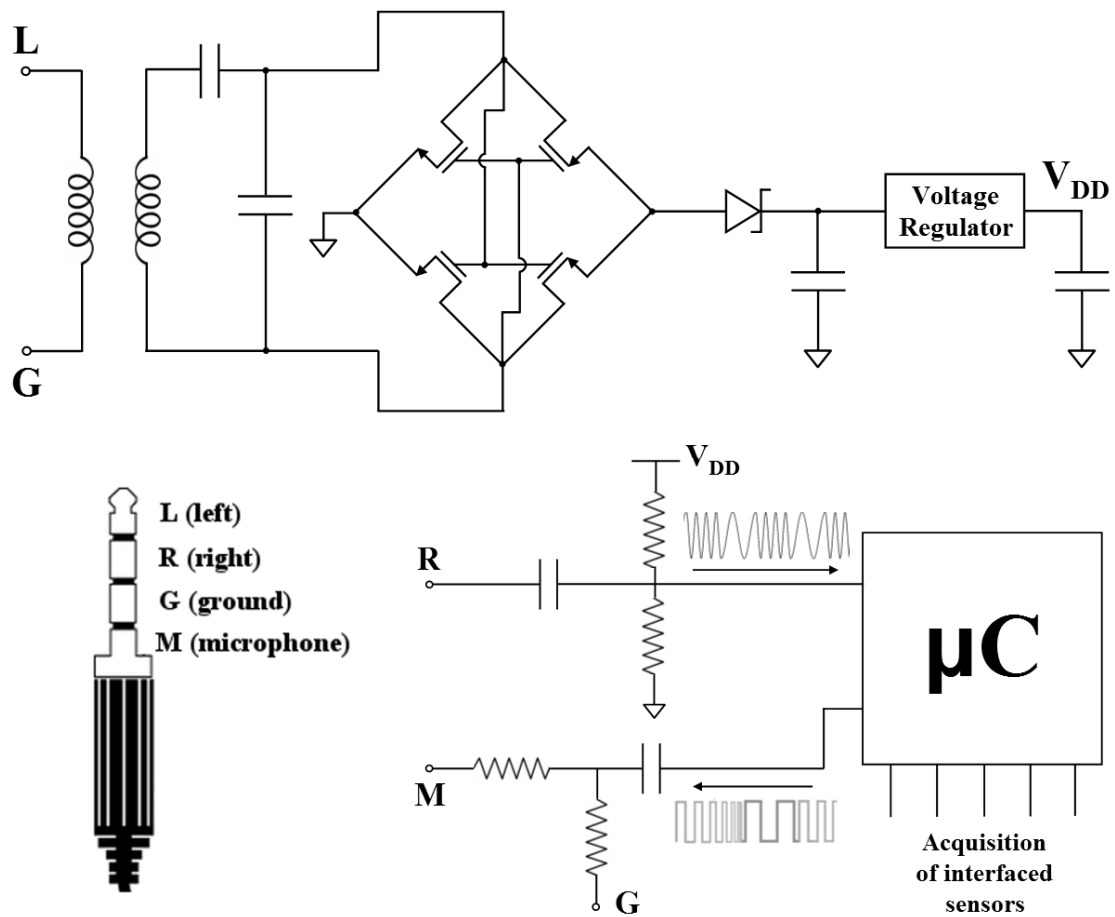


Fig. 5 Schematic of the circuit used for power harvesting and communication using the mobile phone analog 3.5 mm audio jack.

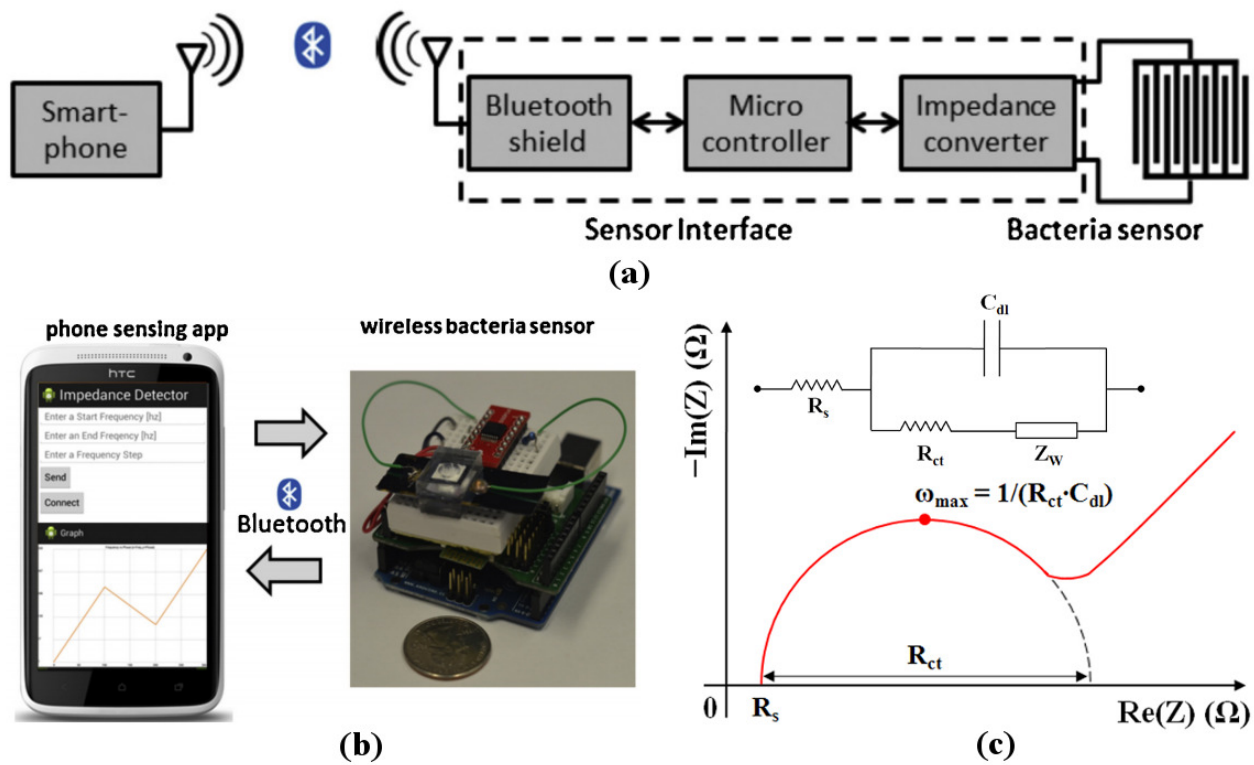


Fig. 6 Bacterial biosensor system using Bluetooth technology to communicate with the mobile phone. Reprinted with permission from [166].

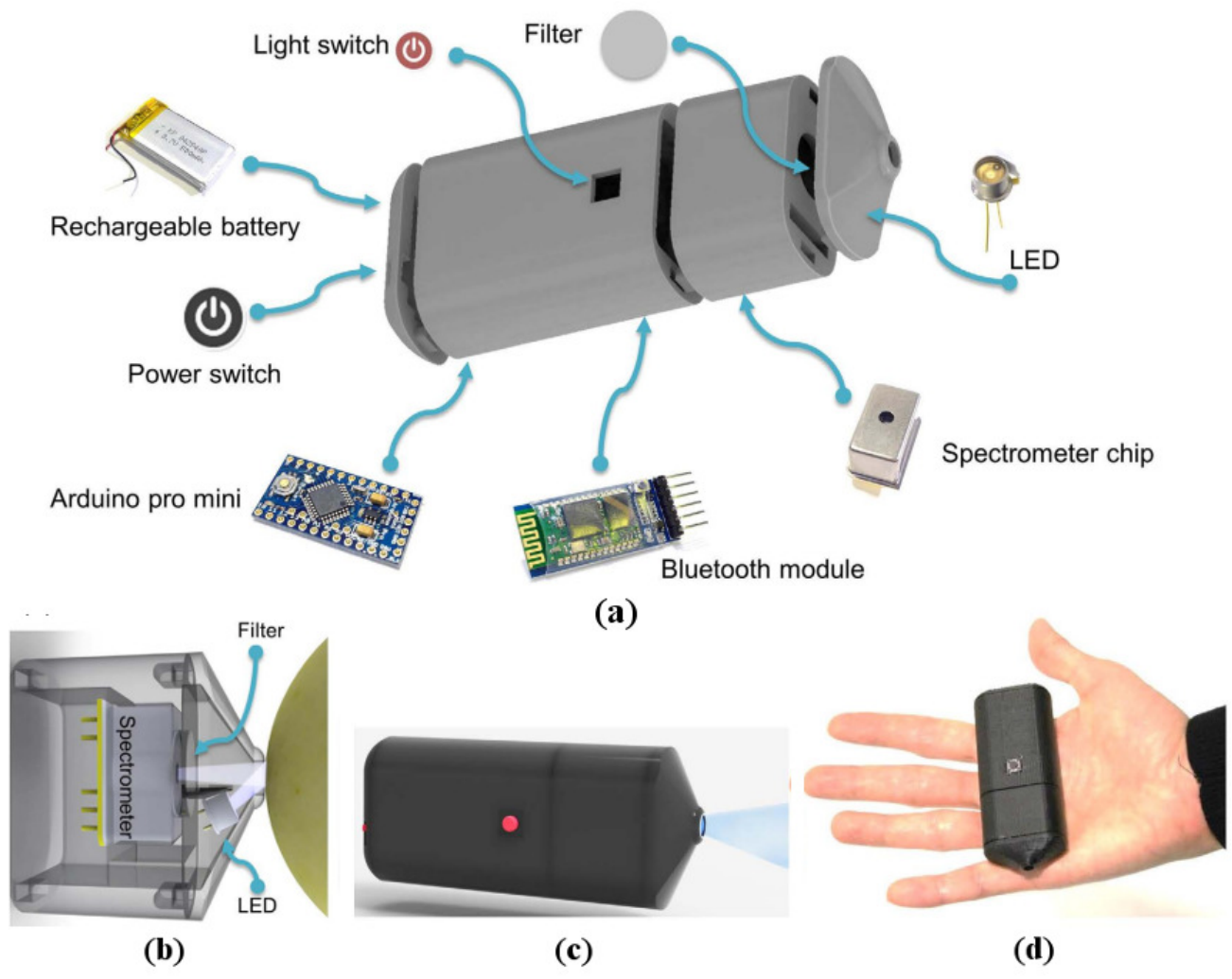


Fig. 7 Smartphone based system for rapid non-destructive testing of fruit ripeness. It uses Bluetooth for communication with the mobile phone. Reprinted with permission from [171].

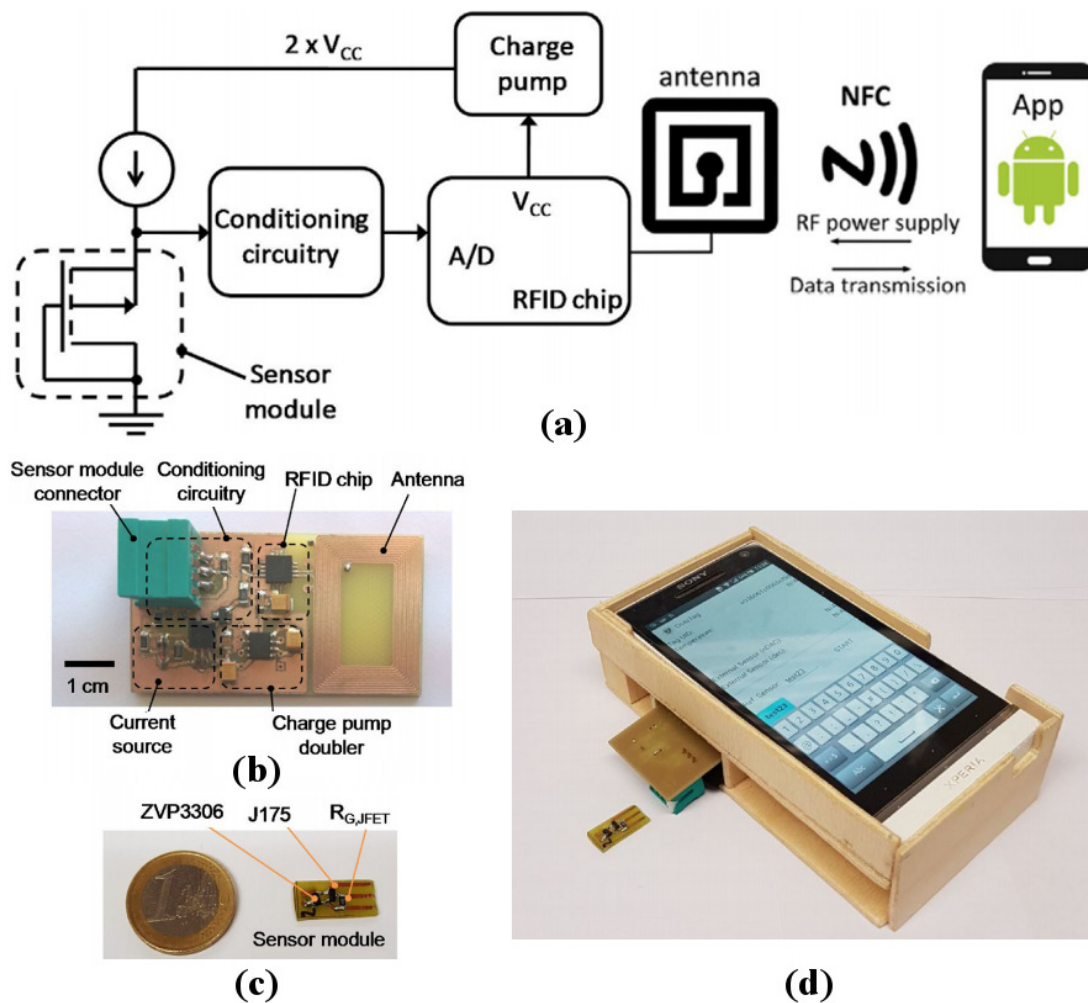


Fig. 8 Compact dosimetric system based on passive NFC tag and smartphone. Reprinted with permission from [186]. The Android robot is reproduced or modified from work created and shared by Google and used according to terms described in the Creative Commons 3.0 Attribution License.

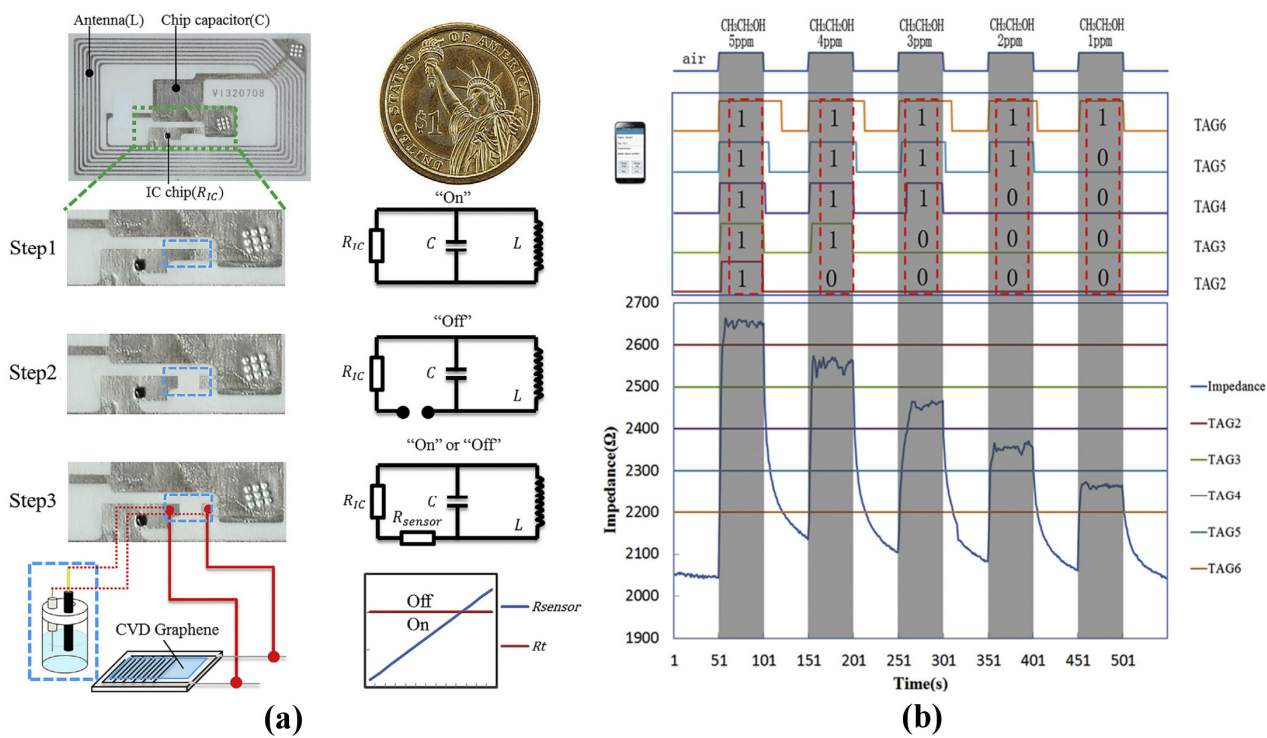


Fig. 9 Passive NFC tag sensor for biochemical sensing with smartphone. Reprinted with permission from [190].

Application	Ref.
Healthcare	[16][17][18]
Sleep screening	[19]
Point-of-care diagnostic	[20]
Optical sensing in resource limited settings	[21]
Treatment of eating disorders	[22]
Food analysis	[23]
Sensors in agriculture	[24]
Biosensors and bioelectronics	[25][26]
Portable spectrophotometers	[27]
Mobile microscopy	[28]
Activity recognition	[29]
Intelligent transportation systems	[30][31]
Road condition monitoring	[32]
Mobile crowdsensing	[33][34][35]

Table 1 Review articles of smartphone based systems for different fields of application.

Working principle	Target(s)	Range of detection	Ref.
colorimetric	pH test strips	0 – 14	[36]
colorimetric	25-hydroxyvitamin D concentration	15 – 110 nM	[37]
colorimetric	alcohol concentration in saliva	0 – 0.3%	[38]
colorimetric	pH, protein and glucose in urine	5 – 9, 0 – 100 mg/dL, 0 – 300 mg/dL	[39]
colorimetric	blood hematocrit level	10 - 65%	[41]
colorimetric	streptomycin concentration in food	50 – 267 nM	[42]
colorimetric	BSA, catalase enzyme and carbohydrate	0 – 1 mg/mL, 0 – 1 mg/mL, 0 – 140 µg/mL	[43]
colorimetric	cloud coverage	4 – 98%	[48]
colorimetric	surface corrosion of iron	N/A	[50]
irradiance measurement	UVA solar irradiance	0 – 10 mW/m ²	[60]
irradiance measurement	UVA aerosol optical depth	0.05 – 0.20	[61]
irradiance measurement	UVB solar irradiance	1 – 9 mW/m ²	[63]
irradiance measurement	atmospheric total ozone column	260 – 320 DU	[65]
irradiance measurement	SO ₂ volcanic emission	0 – 3.5 kg/s	[66]
fluorescence	ochratoxin A concentration in beer	2 – 20 µg/L	[44]
fluorescence	degradation level of olive oil	N/A	[45]
fluorescence	discrimination of different edible oils	N/A	[46]
fluorescence	bisphenol A concentration in water	4.4 – 200 µM	[47]
electrochemiluminescence	2-(dibutylamino)ethanol and L-proline	0 – 5 mM, 0 – 10 mM	[52]
Mie scattering	<i>Escherichia coli</i> in water	10 – 10 ⁵ CFU/mL	[53]
Mie scattering	bacterial concentration in meat	10 – 10 ⁸ CFU/mL	[54]
spectrophotometric	pH for river quality water	6 – 8	[69]
spectrophotometric	BSA protein and trypsin enzyme concentration	0 – 0.30 mg/mL, 0 – 0.30 mg/mL	[70]
spectrophotometric	optical spectrum (color dyes and milk samples)	N/A	[73]
spectrophotometric	Fe ²⁺ in medicine and Na ⁺ in saline solutions	2.93 – 4.76 mg/L, 0.78 – 2.01 mg/L	[74]
spectrophotometric	porcine immunoglobulin concentration	4.25 nM – 3.4 µM	[76]
computer vision	bacterial colony counter	0 – 96 CFU	[79]
computer vision	bacterial colony counter	N/A	[80]
computer vision	bacterial colony counter	0 – 250 CFU	[81]
computer vision	bacterial colony counter	N/A	[82]
computer vision	bacterial colony counter	0 – 500 CFU	[83]
computer vision	surveillance of fruit flies	N/A	[84]
computer vision	food recognition tool	N/A	[85]
computer vision	food recognition and nutritional value	N/A	[86]
computer vision	heart rate measurement	N/A	[87]
mobile microscopy	cell imaging (brightfield and fluorescent)	N/A	[88]
mobile microscopy	image analysis of green algae in freshwater	N/A	[89]

Table 2 Applications of smartphone based systems exploiting the embedded camera.

Working principle	Target(s)	Accuracy	Ref.
sound recording and analysis	chronic lung diseases	average error 5.1%, detection rate 80 – 90%	[90]
sound recording and analysis	chronic lung diseases	average error 8.01%	[91]
sound recording and analysis	number of coughs	detection rate 92%	[92]
sound recording and analysis	respiratory rate	estimation error < 1%	[93]
sound recording and analysis	nasal symptoms	N/A	[94]
sound recording and analysis	snoring quantification	correlation > 0.9	[95]
sound recording and analysis	hearing threshold in noisy environment	N/A	[96]
sound recording and analysis	hearing screening with quality control	detection rate 97.8%	[97]
sound recording and analysis	tremor detection	N/A	[98]
sound recording and analysis	air filter particulate loading	detection rate 80%	[99]
sound recording and analysis	cars approaching pedestrians	detection rate 91%	[100]
non-audio signal processing	oxygen saturation and heart rate	RMS accuracy 0.45 – 0.85%, $R^2 = 0.99$	[101]
non-audio signal processing	histamine concentration in PBS	accuracy 1% in impedance range 120 Ω – 10k Ω	[102]

Table 3 Applications of smartphone based systems exploiting the embedded microphone.

Sensor(s)	Application type	Detection rate	Ref.
GPS	crowd dynamics monitoring	N/A	[103]
GPS	crowd dynamics monitoring	N/A	[104]
GPS	bicycle tracking	N/A	[105]
GPS	driving speed monitoring	N/A	[106]
accelerometer	activity recognition	88%	[107]
accelerometer	activity recognition	70%	[108]
accelerometer	activity recognition	91%	[109]
accelerometer, gyroscope	activity recognition	90%	[110]
accelerometer, gyroscope, magnetometer, linear accelerometer	activity recognition	N/A	[111]
accelerometer, gyroscope, microphone	activity recognition	86%	[112]
accelerometer	fall detection	97%	[114]
accelerometer	fall detection	98.4%	[115]
accelerometer	fall detection	N/A	[116]
accelerometer, gyroscope	fall portent detection	88.5%	[117]
accelerometer	seismic events monitoring	N/A	[118]
accelerometer, magnetometer, GPS	seismic events monitoring	N/A	[119]
accelerometer	structural health monitoring	N/A	[120]
accelerometer	structural health monitoring	N/A	[121]
accelerometer, gyroscope	vibration and cable force tests	N/A	[122]
accelerometer	driver behavior and road conditions	N/A	[123]
accelerometer, gyroscope	driver behavior monitoring	90%	[124]
accelerometer, gyroscope, magnetometer	driver behavior monitoring	96%	[125]
accelerometer, gyroscope, magnetometer	driver behavior monitoring	91%	[126]
accelerometer, gyroscope, GPS, camera	driver behavior monitoring	77 – 91%	[127]
accelerometer, magnetometer, GPS	road conditions monitoring	78%	[128]
accelerometer, gyroscope	road conditions monitoring	98%	[129]
accelerometer, gyroscope, GPS	road conditions monitoring	90%	[130]

Table 4 Applications of smartphone based systems exploiting the embedded accelerometer, gyroscope, magnetometer and GPS.

Communication interface	Target(s)	External hardware	Ref.
USB OTG	heart rate	silver coated dry electrodes	[132]
USB OTG	malaria biomarker PfHRP2 conc.	microfluidic chip and photodiode	[133]
USB OTG	clenbuterol concentration	3-electrodes amperometric immunosensor	[134]
USB OTG	gender verification in human serum	3-electrodes amperometric immunosensor	[135]
USB OTG	metals electrical conductivity and lift-off	custom made impedance probe	[136]
USB OTG	alcohol determination in blood samples	3-electrodes micro potentiostat	[137]
USB OTG	emission properties of iridium complex	electrochemiluminescence sensing system	[138]
USB OTG	detection of nitroaromatic explosives	electrochemiluminescence sensing system	[139]
USB OTG	water turbidity	IR LED powered by USB	[140]
USB OTG	iron(II) and phosphate in water	IR and Vis LEDs powered by USB	[141]
USB OTG	Hg(II) concentration in water	532 nm laser powered by USB	[142]
audio jack	cyclic voltammetry measurements	custom made potentiostat	[147]
audio jack	pH to monitor pulmonary exacerbations	LMP91200 interfaced with two pH electrodes	[148]
audio jack	Hepatitis C core antibody concentration	custom made potentiostat	[149]
audio jack	nitrate concentration in NaOH	microfluidic amperometric sensor	[150]
audio jack	glucose concentration in liquid	electrochemical biosensor	[151]
audio jack	electrochemical measurements	electrochemical sensor and potentiostat	[152]
audio jack	point-of-care diagnostics	multiplexed electrochemical sensor	[153]

Table 5 Applications of smartphone based systems exploiting wired communication to interface with external hardware.

Communication interface	Target(s)	External hardware	Ref.
Bluetooth	heart activity monitoring	ECG electrodes and 3-axis accelerometer	[154]
Bluetooth	cardiovascular disease detection	ECG electrodes	[155]
Bluetooth	pulse rate, blood pressure	homemade blood pressure monitor	[156]
Bluetooth	real-time control of blood glucose	commercial glucose meter and insulin pump	[157]
Bluetooth	real-time control of blood glucose	different commercial glucose meters	[158]
Bluetooth	telecare assessment	pulse oximeter and 3-axis accelerometer	[159]
Bluetooth	fall detection	3-axis accelerometer and barometric sensor	[160]
Bluetooth	air quality monitoring sensor node	temperature, humidity, pressure and gas sensors	[161]
Bluetooth	air quality sensor system	temperature, humidity, light, CO ₂ sensors	[162]
Bluetooth	home security system	Arduino UNO and magnetic switch	[163]
Bluetooth	non-speech body sounds sensing	custom made microphone	[164]
Bluetooth	honey geographic origins	3-electrodes electrochemical sensor	[165]
Bluetooth	<i>Escherichia coli</i> concentration	2-electrodes microfluidic sensor and IC AD5933	[166]
Bluetooth	2,4,6-trinitrotoluene concentration	3-electrodes biosensor and IC AD5933	[168]
Bluetooth	BSA and thrombin concentration	different impedance biosensors and IC AD5933	[169]
Bluetooth	human body fluids compartments	4-electrodes impedance sensor	[170]
Bluetooth	non-destructive fruit ripening state	UV LED and IC C12666MA	[171]
Bluetooth	rapid skin cancer screening	UV LED, white LED and IC C12666MA	[172]
semi-passive NFC	potentiometric measurements	temperature sensor and pH electrode	[181]
semi-passive NFC	glucose concentration using test strips	temperature sensor and pH electrode	[182]
semi-passive NFC	uric acid concentration	temperature sensor and pH electrode	[183]
semi-passive NFC	fluorescein and chloride concentration	LED and photodiode	[184]
semi-passive NFC	low-energy multi sensor measurements	accelerometer, microphone, camera, temperature	[185]
passive NFC	ionizing radiation dose	DMOS ZVP3306 and conditioning circuit	[186]
passive NFC	sweat electrolyte concentration	adhesive sensor patch embedding electrodes	[187]
passive NFC	glucose concentration	amperometric sensor (glucose test strips)	[188]
passive NFC	soil moisture measurement	interdigitated capacitive sensor	[189]
passive NFC	gas detection, bacterial concentration	custom modified passive NFC tag	[190]
passive NFC	NH ₂ , cyclohexane, H ₂ O ₂ , H ₂ O conc.	custom modified passive NFC tag	[191]
passive NFC	NH ₃ , putrescine and cadaverine conc.	custom modified passive NFC tag	[192]

Table 6 Applications of smartphone based systems exploiting wireless communication to interface with external hardware.