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Wound Imaging: Ready for Smart Assessment and Monitoring

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Significance:

We introduce and evaluate emerging devices and modalities for wound imaging and also promising imaging processing tools for smart wound assessment and monitoring.

Recent advances:

Some commercial devices are available for optical wound assessment but with limited possibilities compared to the power of multimodal imaging. With new low-cost devices and machine learning, wound assessment has become more robust and accurate.

Critical issues:

The ability to embed advanced imaging technology in portable devices such as smartphones and tablets with tissue analysis software tools will significantly improve wound care. . As wound care is performed by nurses, the equipment needs to remain user-friendly, enable quick measurements, provide advanced monitoring and be connected to the patient data management system.

Future directions:

Combining several image modalities and machine learning, optical wound assessment will be smart enough to enable real wound monitoring, to provide clinicians with relevant indications to adapt the treatments and to improve healing rates and speed. Sharing the wound care histories of a number of patients on databases and through telemedicine practice could lead to a better understanding of the healing process and thus a better efficiency when the recorded clinical experience has been converted into knowledge through deep learning.

Keywords: wound imaging, tissue classification, mobile health, computer vision, deep learning

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SCOPE AND SIGNIFICANCE

All types of wounds will benefit from the emergence of advanced image acquisition devices and processing tools. As wound care is performed not only in hospital but also at home wound assessment needs to rely on low-cost, user-friendly and portable equipment. We summarize here recent experiments in computer vision laboratories on wound images with emerging image modalities and sensors. A comprehensive review of the introduction and development of imaging in wound assessment helps to understand the power and the limits of this tool in clinical practice.

TRANSLATIONAL RELEVANCE

It is clear that adding information about the wound tends to improve the quality of assessment: each imaging modality extracts specific data to better evaluate the healing process. The assistance of medical experts is still required to provide the ground truth for tuning the image processing algorithms and validating the outputs. At a higher level, the knowledge of these experts is also necessary to combine all the data in order to describe the wound state accurately.

CLINICAL RELEVANCE

The benefits of wound imaging are already visible in automatic wound assessment but the room for improvement is even greater if we consider wound monitoring. To anticipate and favour the evolution of a wound, it is necessary to integrate all its history and to analyse how the different regions, with their different tissue types, have been transformed, how the frontiers of these regions have been distorted and at what speed. By accumulating data, the learning process becomes more robust, enabling more efficient therapeutic options for wound care to be proposed to improve healing rates. We should not nevertheless forget that many other factors influence the wound evolution, in particular all the biological data documented in the patient's medical record. These data need to be included in the learning process to refine wound assessment and monitoring.

OVERVIEW

Evolution of practice

The burden of wound care in the health system

Wound care is a major health issue as it is anticipated that worldwide 380 million people will suffer from wounds by the year 2025. In 2018 in Europe for example, the population prevalence of chronic wounds was 3-4/1000 people, which roughly translates to between 1.5 and 2.0 million of the 491 million inhabitants of the EU, and the annual incidence estimate for both acute and chronic wounds stands at 4 million in the region. There is a wide range of wounds, such as surgical, pressure or decubitus ulcers, venous stasis ulcers, arterial ulcers, diabetic ulcers, and traumatic injuries.

The rising prevalence of diabetes, a pathology associated with a slow healing process, and the growing geriatric population can be considered as the two major factors of the increase in the burden of wound care in the health system, further increased by the rise in the number of trauma injuries and road accidents. As publicly reported wound healing rates are far from reality, the cost could be higher for the health system[1].

These wounds have a major long-term impact on the health and quality of life of patients and their families, causing depression, loss of function and mobility, social isolation, prolonged hospital stays and high treatment costs. Emergency wound care and clinicians with considerable technical skill play a frontline role by performing successful wound care. It is also essential that the wounds be treated promptly and properly for the treatment to be efficient and to improve the wound healing rate. Patients with wounds need frequent clinical evaluation to check the local wound status regularly and adjust therapy. The assessment and monitoring of wounds is therefore a critical task in order to perform an accurate diagnosis and to select a suitable treatment.

Manual assessment

In clinical routine, wound care is performed by nurses as it is done when removing a dressing and cleaning the wound, a time-consuming procedure. As a result, wound assessment suffered for many years from being a strictly manual practice and poor data were available for accurate wound monitoring, especially when the patient was not followed by a single nurse.

The periodic assessment of a wound is based on visual examination: clinicians describe the wound by its physical dimensions and the nature of the different skin tissues involved. Measurements are generally made with a simple ruler, a Kundin gauge, by tracing the outline of the wound on a transparent sheet to compute its area, or more rarely by filling the wound with saline or producing an alginate cast to obtain the volume. Moreover, these methods are imprecise and require direct contact with the wound. Assessing the color and proportion of wound tissues helps to understand the progress of the healing and to provide a contactless quantitative measurement. Within the wound boundary, the healing status is assessed based on a color evaluation model corresponding respectively to the dominant color, i.e. red, yellow, black and pink, of the different tissues found on a wound (respectively granulation, slough, necrosis and epithelium). The ratio of the tissues is recorded on a color coded scale[2]. However, during wound tissue identification, it is difficult for clinicians to determine their precise proportions by a simple visual inspection. Therefore, numerous techniques have become available for tissue classification over the wound region, ranging from the use of tracings to more sophisticated methods requiring the use of cameras and computers.

Pioneering work in optical imaging

Imaging technology started to upgrade wound assessment thanks to the capture of color pictures but it only became common practice with the development of low-cost digital cameras, which also attracted image processing research toward wound image analysis. Many pioneering studies focused on 2D analysis as the wound area can be easily obtained after contour following and a complete segmentation process can provide regions labelled by different tissues after a classification step[3-4-5]. Unfortunately, several drawbacks limit the interest of a simple 2D approach: wounds are not planar and perspective effects degrade area estimation; color constancy is not ensured due to changes in lighting and the spectral response of the sensor. Unless a large image database is created and labelled by medical experts, machine learning of tissue features is poor.

In other work, the problem of 3D reconstruction to obtain wound depth and volume was tackled by two techniques, namely passive versus active vision (Fig.1). In the first case, several images are combined through stereo photogrammetry prototypes to obtain 3D points after matching homologue points in the images[6-7-8]. In the second case, laser or white light patterns such as dots or lines are projected onto the wound and 3D data are obtained over these projections by triangulation[9-10-11]. These techniques still have their limitations, however: these pioneering devices required tedious calibration and were complex, cumbersome and expensive. As wounds have a high prevalence in most hospital services, a large number of compact, low-cost systems are needed. As already mentioned, wound care and monitoring is done by nurses, who need simple procedures and cannot undertake time-consuming assessment on a routine basis. For extensive exams on severe wounds, it is necessary to obtain more reliable diagnosis with an advanced multimodal device.

No work investigated a unified approach capable of dealing both with wound shape and tissue area measurements, the two essential components of a complete wound assessment. Later, a simple digital camera provided at low cost a 3D model of the wound labelled with the different tissues, like a geographic relief map[12-13] (Fig.2). The drawbacks mentioned above were also overcome: auto calibration avoided a tedious calibration step[14] and a reference pattern placed near the wound provided both colour correction and the scale factor[15-16].

Subsequently, no significant improvements were made in the design of dedicated tools for wound assessment as most research still adopted a classical approach and only minor enhancements were reported[17-18-19-20-21]. The emergence of low-cost, accurate, portable and handheld devices was to radically change wound care practice.

First commercial devices for wound care

The first device marketed that adopted a unified approach to some extent was the SilhouetteMobileTM system[22] (Aranz Medical Ltd, New Zealand), (Fig.3 left) which combines a color image with a rough 3D description obtained by three laser lines projected on the wound (Fig.5). However, the color image is only used to obtain the wound outline and consequently an average volume from laser data; tissues inside the wound are not classified to monitor wound appearance. To evaluate its accuracy, a comparison with VisitrakTM (Smith & Nephew, United Kingdom) wound measurement system[23], a tool based on manual tracing on transparent sheets reported onto a tactile tablet, was carried out with a reference provided by an elliptical estimation[24].

For accurate 3D measurements, more data points are required. The WoundZoom (Woundzoom Inc, USA) device is based on a specially designed tablet which contains a built-in 3-D image sensor that can capture the length, breadth and width of a patient's wound. The software program calculates the surface area and volume. It provides professionals with thermal mapping, which is another indicator of tissue health. Recently, InSight[25] (EKare, USA) (Fig.3 right) a device including a compact stereoscopic camera interfaced with an iPad, computer vision and machine intelligence for 3D wound measurement, tissue classification and wound border delineation has been marketed[26].

Emerging acquisition devices and image modalities

Imaging technology progressed rapidly with the emergence of new modalities at reduced cost. Spectral exploration was developed to detect non visible wavelengths, and drastically improved spectral resolution. It provides relevant data for tissue analysis and classification. Concurrent techniques are also available for geometrical measurements on the 3D surface of the wound. The trend is to combine spectral analysis and 3D scanning with multimodal devices.

Spectral exploration: multispectral, hyperspectral, thermal

Acquiring precise wavelengths, about ten for a multispectral image or one or two hundreds in the case of a hyperspectral image, provides much more data than color imaging, which is limited to red, green and blue channels with a large bandpass. These imaging systems, initially developed for remote sensing applications, are now becoming widespread in industry to control manufactured parts or food, and have been applied more recently in the medical field where visible and infrared bands are investigated.

The acquisition technique uses pushbroom sensing, in which the scene is scanned during airborne displacement of the sensor. Since the camera needs to be translated as in a photocopier to obtain a spectrum in each scanned line, this technique is not adapted to wound imaging where the capture of complete image frames is required. To capture a hyperspectral cube, composed of a series of images at different wavelengths, it is necessary to operate very quickly when the scene is not static. A basic and low-cost approach is to use a wheel with several filters to capture in vivo wound images. Even with a few wavelengths, preliminary experimentations on wounds indicated that diagnosis can be greatly improved with spectral discrimination[27]. Manual filter selection can be avoided with liquid crystal filters which are electronically tuned through a computer interface. This technique proved to be efficient to explore which wavelengths are relevant to detect and display vital tissues during surgery in an operating room[28]. Recently, advanced snapshot mosaic sensors[29] (IMEC, Belgium) have been marketed. As they allow a series of wavelengths to be captured simultaneously in the visible and near infrared band, medical applications will undoubtedly benefit from this technology. Another technique to gather tissue response to specific wavelengths is to illuminate the tissue with these wavelengths in a dark environment. For example, based on digital light processing videoprojection, a hyperspectral imaging system has been designed for visualizing the chemical composition of in vivo tissues during surgical procedures, in particular to quantify the oxygenation of the tissues[30]. In a recent study, monitoring wound healing in a 3D wound model by hyperspectral imaging was investigated. An in-vitro 3D wound model was established and incubated without and with acute and chronic wound fluid. The model was able to correlate cell quantity and spectral reflectance during wound closure[31].

The number of wavelengths provides sharp discrimination between tissues but the ability to stimulate tissues with only a particular wavelength can reveal hidden properties. This is the case of the i:X Wound Intelligence device[32] (MolecuLight, Canada) (Fig.4). With the guidance of fluorescence imaging, this portable touch-screen with an intuitive interface allows clinicians to quickly, safely, and easily visualize bacteria. They simply appear in red in the image, providing maximum insights for accurate treatment selection. The device emits a precise wavelength of safe violet light, which interacts with the wound tissue and bacteria, causing the wound and surrounding skin to emit a green fluorescence and potentially harmful bacteria to emit a red fluorescence. A similar approach is followed in the SnapshotNIR device[33] (Kent Imaging, Canada) (Fig.5) which uses light in the near-infrared spectrum for wound assessment. As the wavelength dependent light absorption of haemoglobin differs if it is carrying oxygen from when it is not, this device displays images of oxygen saturation. It gives access to tissue perfusion and blood flow which are key factors for clinicians to determine the course of treatment for a chronic wound.

Higher wavelengths in the infrared band provide thermal information. As new devices become more and more affordable and are now integrated in compact modules, thermal cameras are becoming common for industrial control and visual inspection. This imaging modality is particular relevant for wound assessment and has been investigated in this field[34-35-36]. It allows for physical and physiological monitoring, feeding information to the physician about blood flow and metabolic activity and it helps to identify differences between affected and unaffected tissues. The Scout solution[37] (Woundvision, USA), for instance, is a visual and infrared imaging device that measures and records wound size and pathophysiological changes reflected in the underlying tissues, based on temperature differential. In the current European STANDUP project[38] (Smartphone Thermal ANalysis for Diabetic Foot Ulcer Prevention detection and treatment) dedicated to diabetic foot ulcers[39] (Fig.6), thermal information is used to prevent ulcers by hyperthermia detection, to monitor ulcer healing by combining thermal, colour and 3D measurements and to improve the design of foot insole and foot pads.

We do not consider non optical modalities in this paper but we should mention the combination of high frequency ultra sound with colour images, as ultra sound provide complementary knowledge on the nature of underlying tissues[40] and ultrasound elastography provided images which can enable pressure ulcer early detection[41].

3D geometrical measurements: shape from motion, pattern projection, time of flight cameras, plenoptic cameras

A single image provides a lot of information on a wound but it fails to produce accurate shape measurements, due to perspective projection errors on non planar wounds. To obtain 3D data, many approaches are now possible.

By combining several images from different points of view, 3D points can be reconstructed by triangulation. This is the basic concept of stereoscopic systems. Nowadays, the acquisition of image pairs can be advantageously replaced by video acquisition, since in an image sequence the mapping of homologous points is easily done between two successive images, whereas it is often tricky to find corresponding points between distant viewpoints. The weak point of this technique is that it does not work if the wound is insufficiently textured: not enough points can be matched between the images, resulting in a sparse 3D map and poor measurements. On well textured scenes, this shape from motion approach competes with powerful laser scanners equipped with turning tables, as tested in a study on volume estimation of skin ulcers[42] (Fig.7).

To ensure more robust results than with the preceding passive vision techniques, in active vision light patterns are projected onto the wound to obtain a 3D shape from the distorted pattern. This is the solution embedded in the commercial wound assessment device Silhouette (Aranz Medical, New Zealand) which projects three laser lines to obtain wound 3D data. The projection of a textured pattern provides denser 3D maps for accurate volume estimation, as done with the Insight device (EKare, USA).

Recently, affordable time of flight cameras became available. These cameras are so named because they produce depth images by measuring on each point the time taken by light to reach this point and be reflected back to the sensor. These devices have been advantageously compared to manual techniques for wound volume measurement[43]. This is also the case in a new multimodal prototype sensor system for wound assessment and pressure ulcer care. Multiple imaging modalities including RGB, three-dimensional (3-D) depth, thermal, multispectral, and chemical sensing are integrated into a portable hand-held probe for real-time wound assessment It performs various assessments including tissue composition, 3D wound measurement, temperature profiling, spectral, and chemical vapor analysis to estimate healing progress[44].

Another class of sensors could soon revolutionize photographic devices. It is constituted by newly manufactured plenoptic sensors[45], (Raytrix, Germany), which are already integrated in industrial inspection tasks. Whereas a classical digital camera measures on given pixel the total intensity of light emitted from one point of the real scene, a plenoptic camera also captures in a single snapshot the direction of each ray contributing to the intensity on a pixel, called the light field.

It enables super-resolution with multi-view stereo, all in-focus, less occlusion with variable baselines and depth maps for metrically correct measurement. In the near future, this technology could be integrated in smartphone cameras as light field modules for smartphones have aroused the interest of manufacturers. These tools are very promising for medical applications. For example, in soft-tissue surgery, a novel fused plenoptic and near infrared camera tracking system enables three-dimensional tracking of tools and target tissue while overcoming blood and tissue occlusion in the uncontrolled, rapidly changing surgical environment[46].

Machine intelligence for tissue segmentation

Expert knowledge

When wound assessment is done during visual examination, the clinician's knowledge is required to characterize the nature of the tissues. Even with the naked eye, an expert is able to discriminate between healing and infected tissues under non controlled lighting, but his/her efficiency is limited to producing quantitative measurements over the wound status or evolution. Wound imaging enables automatic measurement of tissue areas but tissue classes need to be first defined. Clearly, the expert knowledge needs to be transferred to the machine vision system by a learning step. It consists in collecting certified samples of each class of tissue to constitute a tissue database.

The clinician can draw tissue outlines on digital wound images but this process is time consuming. One alternative is to label previously segmented images with one of the tissue class labels. The clinician is no longer free to delimit exactly tissue regions but if the segmentation level is small enough, one can avoid creating hybrid regions containing several tissue classes, which the clinician would be unable to label. Note that intra-observer repeatability is not maximal in this process and that inter-observer repeatability is even lower, so that several experts are needed to produce a robust ground truth. Tissue regions with poor consensus should be discarded for the learning step.

Machine learning

A wound database is built from part of the labelled sample tissues. Then machine learning is run and validated by automatically segmenting the other part of the samples called the test database. Building a tissue model requires manually extracting color and texture descriptors to characterize each sample and assign the correct tissue label to it. A machine learning approach is still very popular and forms the basis of many successful commercially available medical image analysis systems. The support vector machine (SVM) is the most popular supervised algorithm, and typically exhibits the highest performance for most classification problems, given its advantages of regularization and convex optimization. Various machine learning models have been created to perform wound tissue classification. For example, a robust skin tissue classification tool using cascaded two staged SVM based classification was proposed[15]. The segmentation task was performed by extracting texture descriptors and color descriptors from wound images, followed by the SVM classifier to classify the different tissues within the wound into three types (granulation, slough and necrosis). Similarly, computer methods based on manually engineered features or image processing approaches were implemented for the segmentation of diabetic foot ulcers (DFU).

Convolutional neural networks

A crucial step in the traditional machine learning workflow is the selection of discriminant features from the images. This process is still done by humans. On the other hand, with deep learning, the so called new generation of neural networks, manual feature engineering is not required. Instead, the network learns on its own by processing the high-level features from raw data, but massive image databases are required for the learning step.

After the success of deep learning in other real-world applications, it is also providing exciting solutions with good accuracy for medical imaging and is seen as a key method for future applications in the health sector[47]. Traditionally, scientific discoveries are the result of intuition and observation, making hypotheses from associations and then designing and running experiments to test the hypotheses. However, with medical images, observing and quantifying associations can often be difficult because of the wide variety of features, patterns, colours, values and shapes that are present in real data. Here, deep learning can extract new knowledge from the accumulation of hundreds of thousands of real cases. Deep learning in healthcare covers a broad range of problems and provides doctors with an accurate analysis of any disease, helping them treat them better, thus resulting in better medical decisions. It is noteworthy that the number of papers published on a wide variety of applications of deep learning in medical image analysis[48] grew rapidly between 2015 and 2017. The most widely used type of deep learning model for medical image analysis is convolutional neural networks (CNNs). Deep learning can contribute to a range of canonical tasks in medical image analysis: classification, detection, segmentation, registration, retrieval, image generation and enhancement. For example, using deep-learning models trained on patient data consisting of retinal fundus images, it is now possible to predict cardiovascular risk factors not previously thought to be present or quantifiable in retinal images, such as age, gender, smoking status, systolic blood pressure and major adverse cardiac events[49]. Deep learning can more directly outperform an expert eye in the detection of pathologies during breast, liver, and lung radiological exams. As X-ray images provide huge amounts of data, CNNs can rise to the challenge of identifying very small regions in images depicting anomalies, such as nodules and masses that might represent cancers. Compared to highly trained dermatologists, deep neural networks also obtained similar diagnostic accuracy in identifying several types of skin cancers but it involved a huge reliably annotated image database which is not currently available for wounds[50].

Image segmentation is one of the first areas in which deep learning displays promising contributions to medical image analysis and some pioneering studies have recently investigated this approach (Table 1). As deep learning requires a massive amount of training data, which is a real problem for wound images captured in the patient room, several strategies have been tested to overcome it:

One solution is to split large images into small ones to expand the size of the database. Geometrical transformations such as scaling, translations, rotations, flipping, elastic deformations or color space changes can also be made to generate a lot of sub-images. In a recent study[51], (Fig.8) only 22 images of pressure injuries were used for tissue classification (granulation, slough, and necrosis). The method involved using CNN on a large number of small dataset images to perform optimized segmentation. The training and test images had a standard resolution but a pre-processing step created a set of small sub-images which were used as input for the CNN network which achieved an overall average classification accuracy of 92%.

Another solution is to pre-train the network on a very large scale generic image database before training it on a smaller one dedicated to the application. A two-tier transfer learning method was applied by training a fully CNN on larger datasets of images and using it as pre-trained model for the automated segmentation of diabetic foot ulcers[52]. A dataset of 705 images was constituted, including 600 diabetic foot and 105 healthy foot images. The surrounding skin was also considered as it is an important indicator to assess the ulcer's progress. The specificity value for ulcer tissue was around 98%.

Expanding the training sample by geometrical transformation does not account for variations resulting from different imaging protocols and lesion specificities. So, a third solution takes advantage of a particular class of networks called generative adversarial networks (GAN). Composed of a generative model G and a discriminator model D, they have the ability to explore and discover the underlying structure of the training data and learn to generate new realistic images for network training using the G model. This is particularly interesting for wound imaging where data scarcity and patient privacy are important concerns. The discriminator D can be seen as a regularizer to ensure that the synthesized images are valid[53]. This approach has been tested for unconditional dermoscopy image synthesis prior to skin tissue classification[54].

One interesting result is that while CNN outperforms classical machine learning for wound segmentation and even feature extraction, SVM should be preferred for the next step of tissue classification. For example, the classification was a two-step process: AlexNet as a pre-trained network for feature extraction and SVM with a linear kernel for tissue classification[55]. The dataset of wound tissues consisted of 350 images labelled into 7 types. Current wound segmentation methods assume that there are only 3 tissue types (Necrotic, Sloughy, and Granulation) present at the wound bed, but adding other tissues (healthy granulating, unhealthy granulating, hyper granulating, infected, and epithelial) refines the classification. Using the pre-trained DNN AlexNet as feature extractor resulted in better classification accuracy compared to conventional features (86.4% as opposed to 79.66%). Similarly, (Fig.9) a wound segmentation technique was developed[56], based on a CNN model whose features were then used in infection detection via SVM classifiers and in the healing prediction process via Gaussian process regression. For wound segmentation, CNN achieved better accuracy compared to the SVM classifier (95% as opposed to 77.6%), whereas for wound infection detection, the SVM classifier trained with CNN features achieved a total accuracy of 84.7%. In fact, CNN should involve traditional image processing in the image processing workflow, for instance for environmental background removal in preprocessing step and semantic correction in a post-processing step[57].

Wound Image Management

Image databases

In the field of medical imaging, while a number of open access datasets are available, most of them are related to radiology (X-rays, MRI, PET, CT …) and not wound imaging. However, such databases would be valuable for research especially when machine learning and artificial intelligence are involved but also to enable the comparison of algorithm efficiency from concurrent research teams through challenges or simply for publication reports. In a scientific study, a research team works on its own image database and so it is difficult to compare algorithm performance. Moreover, the quality of the ground truth cannot be checked by other teams.

There are several reasons for this: firstly, wound images are difficult to obtain as they are taken at the bedside (it is not pleasant for the patient to face a camera with such a handicap and taking pictures is often only possible when the dressing is changed by the nurse); secondly, as these images are difficult to obtain, researchers are tempted to reserve their exploitation to their own group; thirdly, there is a lack of standardization in the protocols for wound image capture: lighting control, points of view and centring, scale factor, colour constancy, wound history, patients' medical records, etc. are all features that can vary from one study to another. All these points should be addressed. Not only are wound images already difficult to find, but obtaining series of images covering a wound history from its inception to healing is nearly impossible.

Some wound images can nevertheless be retrieved from the Medetec wound database[58]. It contains free stock images of all types of open wounds such as venous leg ulcers, arterial leg ulcers, pressure ulcers, malignant wounds, dehisced wounds resulting from surgical wound infection, skin or microvascular changes associated with diabetes, diabetic ulcers, ischaemic wounds regularly encountered by a wound care practitioner. A complementary database named Medetec Surgical Dressings Database contains stock images of surgical dressings and other types of wound dressings such as hydrogel dressings, hydrocolloid dressings, alginate dressings, as well carbon dressings or those containing silver or other forms of antimicrobial or antibacterial agents used to promote wound healing.

Computer aided wound monitoring

At the beginning, a precise wound assessment is a prerequisite for wound monitoring. Many components of the assessment should be included in weekly documentation through a nurse's narrative note or a wound assessment chart: wound location, aetiology, classification or stage, size of wound (length, width, and depth), amount of wound tunnelling and undermining, type of tissue and structures observed in the wound bed, amount of exudates, state of the surrounding skin and wound margins, signs and symptoms of wound infections, individual's pain level, patient's medical factors which could delay healing and treatment objectives.

Clinicians, when tracking the recovery of healing wounds, must have a standard procedure for recording the wound's progress throughout the various healing stages. The two major procedures for wound assessment are the PUSH and BWAT tools. The Pressure Ulcer Scale for Healing (PUSH) tool for standardized wound measurement, developed by the National Pressure Ulcer Advisory Panel, indicates whether a wound is worsening or improving over time. The sum of each of the 3 sub-scores (surface area, exudate amount and tissue type) comprises the total PUSH score which is recorded and used to track healing. Similarly, the Bates-Jensen Wound Assessment Tool (BWAT) uses the scoring of 13 factors to determine the state of a wound (size, depth, edges, undermining, necrotic tissue type, necrotic tissue amount, exudate type, exudate amount, skin color, oedema, induration, granulation and epithelialization).

After wound assessment, evaluation of care and a wound treatment plan can be investigated. Wound imaging provides only one component of a patient's state and can obviously not determine if the treatment has to be changed. With the commercial devices currently available in the clinical environment, only global parameters such as wound dimensions and the proportion of the different tissues are extracted. Analysing locally and over time the distribution of the different tissues and the evolution of the 3D surface could improve understanding of the healing process and diagnosis. The accumulation of a great number of wound healing histories including all the wound assessment components could feed machine learning algorithms to assist the clinician in treatment decision

Wound monitoring quality can be significantly improved when the wound imaging device is linked to a data management tool. For example, the WoundZoom tablet[59], through its Web portal, helps collate patient information and can be easily integrated with a hospital's electronic health records, which is vital to creating a seamless digital network and eliminating double documentation. Data can be exchanged between hospitals or between patients at home and clinicians. Several clinical centres have experimented the benefits of telemedicine for skin pathology diagnosis or monitoring the wound therapy. For this reason, it is relevant to collaborate with pioneers in telemedicine environments[60]. Currently, images are shared through networks with other hospitals or patients at home and videoconferencing is supported but no image processing apart from data compression has been applied on the captured images. With the development of mobile health, patients with chronic wounds who need the evaluation and assessment of a wound care specialist can take photographs of the wounds with a digital camera or smartphone and send them via the internet to the wound care specialist. These digital photographs allow the expert to diagnose and evaluate the chronic wounds on a periodic basis. Nevertheless, it is necessary to be aware of a degraded reliability when performing wound assessment using mobile images[61].

Smartphone applications

Digital cameras are tending to be replaced by smartphones for image capture, as these low cost and familiar devices now support powerful embedded processing and inherent data transmission capabilities. A smartphone is not as reliable as a high-grade medical imaging device but it is the instrument of choice for mobile health[62-63]. The range of applications is also extended by add-on or connected sensors.

For example, smartphones are used for acuity screening in rural areas. Moreover, retina health can be monitored by plugging a small portable ophtalmoscope for macula and optic nerve illumination into the smartphone[64]. In orthodontics, it is now possible to use mouth pictures taken at home by the patient him/herself, which are then uploaded and processed to analyse tooth movements[65]. A lot of sensors are embedded in a smartphone and have been used for medical applications such as patient tracking at all times with GPS to deal with the risk of wandering or patients' balance monitoring using the phone's accelerometer.

Smartphones or tablets are indeed promising tools for standard wound monitoring at the patient's bedside in hospital or at home[66-67-68]. It is clear that sophisticated equipment could enable more accurate ulcer detection or assessment than a smartphone but none of it is designed for mobile health applications (mHealth). So, the challenge is to embed in a smartphone the essential features required by the nurse to rapidly assess an ulcer, characterize its evolution, transfer measurements to the hospital data management system and obtain therapeutic indications.

Wound management

With the development of eHealth, smartphones and tablets are appropriate tools for wound management when mobile and connected devices are looked for. For the nurse responsible for wound care, it becomes a personal organizer and secretary. Several software tools have been developed to simplify wound management.

The smartphone can replace paper-based charting with electronic charting for chronic wounds. It facilitates telehealth with data sharing and data transfer between multiple healthcare providers, allowing for more timely consultation and reducing the need for patients with mobility difficulties to attend consultations in person[69].

Wound treatment, team communication and quality reporting can be simplified if clinical data and images are captured via a handheld device at the bedside. Clinically validated tools such as the Braden scale for predicting pressure ulcer risk and the PUSH tool for monitoring wound healing can be integrated in a bedside wound management and risk prevention system. Patients are sorted by overall risk and the nurse will even be prompted to deliver patient interventions[70].

An mHealth application for decision-making support in wound dressing selection has also been proposed, so that the nurse can be assisted at the patient's bedside[71].

Wound imaging without add-on sensors

To comply with the concept of mobile health (mHealth), one should ideally use nothing but a smartphone, excluding add-on sensors, especially if use by patients at home is intended. Some advanced imaging modalities are then excluded but automatic wound assessment is nevertheless possible.

To obtain geometrical measurements of the wound with this limitation, several solutions were evaluated[72]. A mobile application to document chronic wounds using a smartphone was extended to facilitate geometrical measurements on wounds using the smartphone's integrated camera. Three approaches to image analysis were developed and evaluated: computing depth using autofocus data, a custom sensor fusion of inertial sensors and feature tracking in a video stream and a successful custom pinch/zoom approach.

In commercial applications for 3D reconstruction without add-on sensors, the technique is based on photogrammetry: the user takes a series of pictures from different viewpoints and a 3D coloured and textured model of the object is derived by computation using such popular applications as QLone[73], Scandy Pro[74] or Scann3D[75]. A video acquired with a high-tech smartphone can compete with a laser scanner if the wound tissue is sufficiently textured to enable dense 3D map reconstruction[42].

For wound tissue segmentation purposes, the embedded processing power of recent smartphones is now sufficient to implement powerful algorithms. For example[76], the smartphone can perform wound segmentation by applying the accelerated mean-shift method. Within the wound boundary, the healing status is next assessed based on a red-yellow-black color evaluation model. Moreover, the healing status is quantitatively assessed, based on a trend analysis of time records for a given patient

Another efficient algorithm, the random forest classifier based on various color and texture features has been implemented on mobile devices to classify necrotic, sloughy, and granular tissues. Although the training phase is time consuming, the trained classifier performs fast enough to be implemented on a smartphone[77].

Wound imaging with add-on sensors

A smartphone is able to perform wound 3D scanning with the emergence of software applications and add-on sensors. These advances are mainly driven by new face identification functions embedded into the smartphone but the translation to medical applications is immediate. With add-on sensors, the current technique available is structured light where a light pattern is projected onto the scene.

For example in the Structure Sensor[78] from Occipital (Fig.10 top) integrated in the TechMed3D medical application intended for body parts digitization, the structured light consists of an infrared speckled pattern which gives access to multiple custom measurements and scans exportation into iMed files. In the Eora 3D scanner[79] a green laser line generator attached to the smartphone provides structured light but the part to be scanned needs to rest on a turn table to obtain a complete scan, so this technique is not applicable to a patient. The most accurate technique is time of flight (TOF) (Fig.10 center). The time it takes for the emitted light pulse to return to the sensor is measured to compute the depth in different directions and accurately map objects through a purely geometrical mesh. This technique is embedded in Vivo's TOF 3D camera[80] that will soon be available for smartphones, and featuring a 300,000 pixel resolution depth, which is said to be 10x the number existing in structured light technology.

Compact add-on thermal sensors have also been marketed for Android and IPhone smartphones. For example, in the STANDUP European project[38] currently in progress, thermal information is provided by a compact Flir one PRO (Fig.10 bottom) camera[81] plugged into an Android smartphone. Two smartphone applications are currently being developed. The first one will be able to detect possible hyperthermia of the plantar foot surface and will analyze temperature variations on targeted regions of interest. The local temperature differential between the two plantar arches and also temperature variations just after a cold stress test are analysed for screening purposes. The second one will assess temperature, color, and 3D shape of DF ulcers over time. The integrated camera provides colour imaging and 3D measurements should be obtained from video capture and compared for evaluation to an add-on sensor plugged into the smartphone.

The design and adaptation of other sensors for smartphones is still in progress to overcome technical challenges. This is the case for optical coherence tomography technique which proved to be relevant for monitoring of wound healing processes in biological tissues[82] and is now addressed by sensor manufacturers for the mHealth market[83].

DISCUSSION

When faced with the ongoing revolution in imaging devices and software tools for wound assessment, one may legitimately feel somewhat bewildered. When digital cameras replaced traditional photography, the advantages of numerical files over printed pictures were obvious. The reduction in cost to make a picture was drastic and the digital file could be stored, shared and transferred easily and quickly. Recently, new imaging modalities have emerged at reduced costs and are very promising for wound care. So, which devices should reasonably equip clinical staff in the coming years?

Until recently, the primary or secondary endpoints in wound research were largely based on time-to-closure or overall area reduction. The automatic measurement of volumetric changes and the progression of tissue composition have changed this situation. 3D wound scanners and tissue segmentation and classification software must therefore be integrated in the weekly wound assessment.

A major point is the need for low-cost, user-friendly imaging devices: given the high prevalence of wounds in hospitals, these devices need to be routine equipment for nurses, like a thermometer or tensiometer. Considerable time is already devoted to dressing the wound so there is little extra time to spend on capturing and processing images. The same criteria also apply for mobile health development: the patient should be able to operate the device easily.

Another essential point is the need for data exchange: the imaging device has to be connected with the hospital data management system. This is particularly important when several nurses take care sequentially of a group of patients. The constitution of large wound databases for machine learning purposes is also dependent on the dissemination of wound images at a very large scale as the efficiency of new deep learning techniques relies on the number of sample images used during the learning step.

The superiority of multimodal imaging tools is also relevant. Combining several wavelengths and 3D geometrical measurements helps to develop a more robust wound description than that obtained with a single sensor.

For these reasons, tablets and smartphones are the best platforms for wound assessment at the bedside or at home. As more and more computing resources, imaging technology and sensors are embedded in these devices at reduced cost due to large scale production, they will play an increasing role in wound assessment. Some functions such as thermal imaging, bacterial activity or oxygen saturation display could be reserved for therapeutic follow-up of severe wounds; at least add-on sensors for smartphones can be shared easily by the clinical staff.

The next frontier will be advanced tools for wound monitoring and treatment plan assistance. Optical assessment of wounds is generally limited to a static evaluation: the knowledge of wound history, including its geometric evolution and temporal changes in the tissues are not taken into account to fine tune the diagnosis, except for graphs of global parameters such as wound size or the proportion of each type of tissue over time, and wound history is often summed up by scores such as PUSH or BWAT. Taking the local changes in wound geometry and tissue distribution over the wound surface into account could improve analysis of the healing process and help to adapt treatment.

In conclusion, we should not forget that optical imaging remains only one component of wound assessment among those listed in the clinical chart and that all the biological and health data in the patient's record contribute to devising an efficient treatment plan to optimize wound healing.

SUMMARY

Wound assessment no longer relies only on manual measurements as optical imaging has demonstrated its efficiency to measure the 3D geometry of wounds and to identify the biological status of tissues. However, in order to be routinely used in the clinical setting, compact, user-friendly and low-cost devices are required, as wound care is performed by nurses and wound prevalence is high among patients. Low-cost multimodal devices and advanced technology now address compact thermal, hyperspectral and range imaging issues. Multimodal systems will not merely add but will multiply benefits, for accurate and robust wound assessment. The emergence of deep learning is also expected to be promising for tissue analysis.

The commercial devices available for wound care are unsurprisingly somewhat less advanced but the gap will be filled rapidly. In fact, the economic pressure on the health system will have a great impact on the solutions available in coming years and mobile health should undergo a spectacular development with the integration of enhanced imaging hardware and software tools in smartphones.

Mary Ann Liebert, Inc., 140 Huguenot Street, New Rochelle, NY 10801

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Figure legends

Wound Imaging: ready for smart assessment and monitoring

Figure 1: volume measurement: active vision by color stripes projection (MAVIS I) passive vision by dual lens stereovision (MAVIS II)

Figure 2: 3D wound reconstruction and labelling using a simple handheld digital camera

Figure 3: (left) Silhouette wound assessment device from Aranz medical (right) InSight device device from EKare

Figure 4: Diabetic Foot Ulcer, Heel - FL-image revealed both cyan fluorescing bacteria which is indicative of Pseudomonas aeruginosa (arrows) and red fluorescing bacteria *MolecuLight i:X Wound Intelligence Device*

Figure 5: Snapshot NIR allows viewing oxygen saturation (StO2) levels throughout the wound and surrounding tissue. Kent Imaging Snapshot$_{NIR}$ device

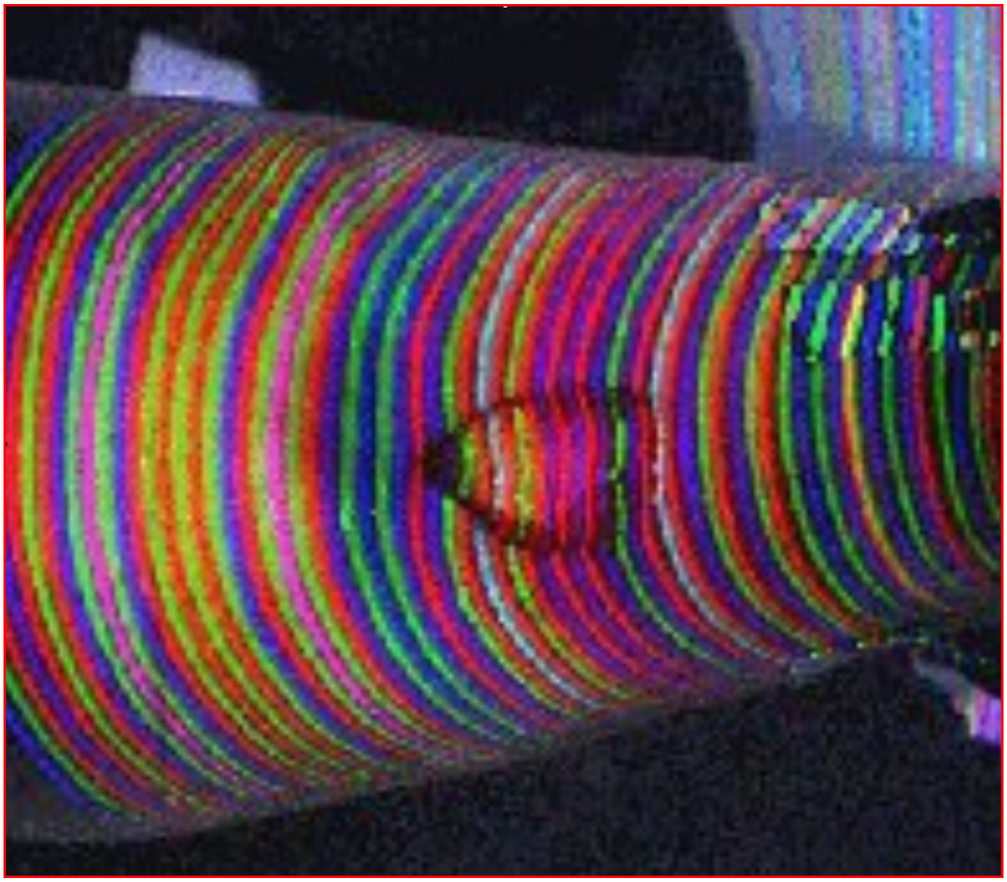
Figure 6: From an infrared feet image with a smartphone equipped with add-on thermal sensor (left) temperature differential can be computed (center) to detect hyperthermia for diabetic ulcer prevention

Figure 7: Reproducibility test: Residual distances between 3 models generated from dfferent mobile cameras after ICP registration with the laser scanner reference (top left) - Zenteno 2017

Figure 8: Pre-processing step for database creation (top) and dataset dictionary for three wound tissues (bottom) - Zahia 2018

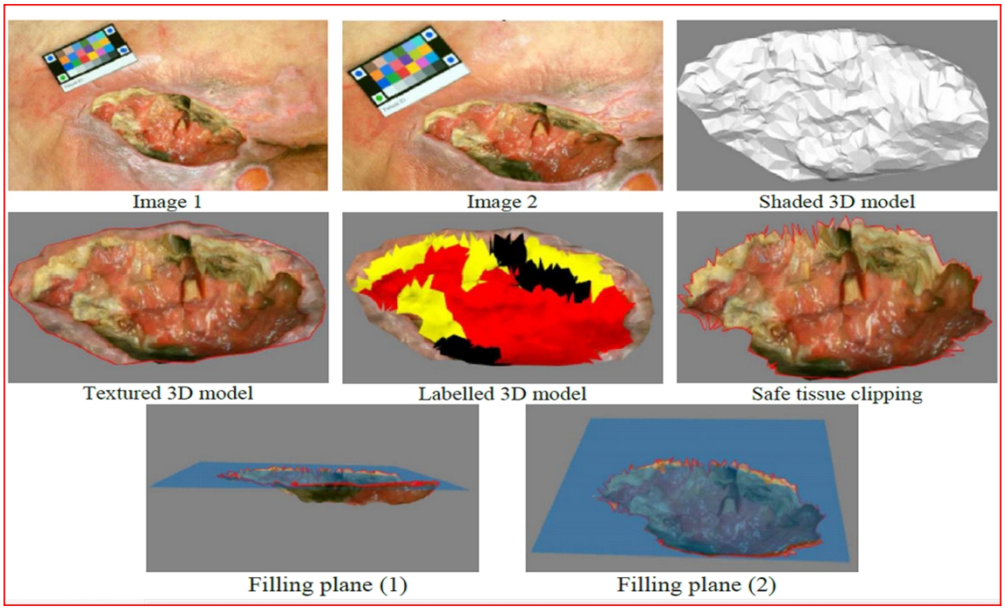
Figure 9: (from left to right) The cropped image is taken as input by the neural network- At the output pixel-wise probabilities of wound segment are provided in grey levels the and final mask is obtained by setting a threshold of 0.5 on every pixel, to compare with the ground truth mask displayed in the last column. Wang 2015

Figure 10: Structure Sensor by Occipital mounted on a tablet (top) Vivo's TOF 3D sensor for smartphone (center) Flir One PRO LT thermal camera for IPhone and IPad (bottom)



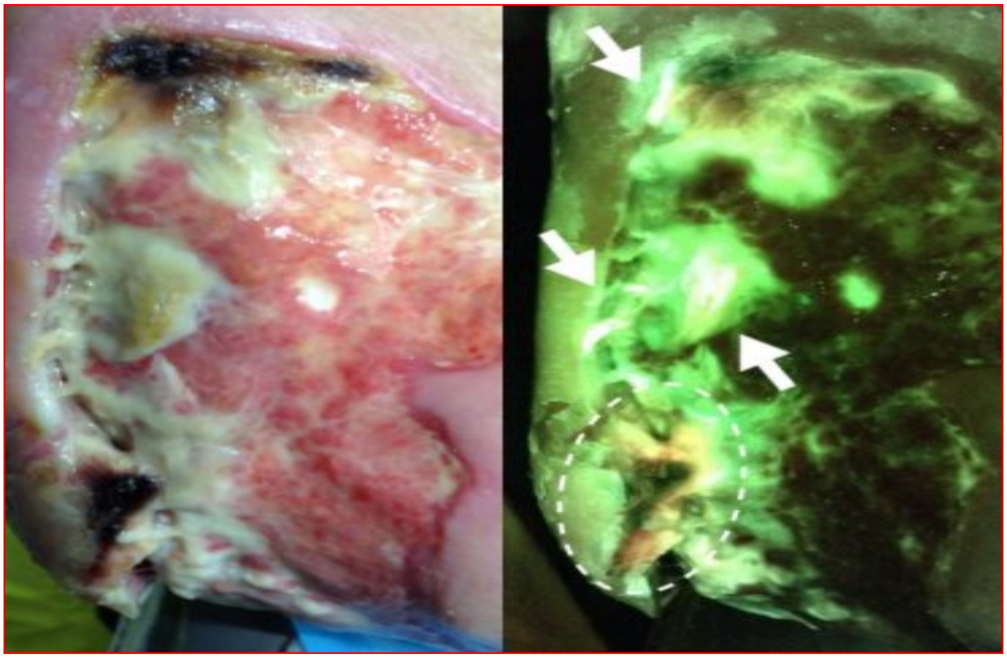
volume measurement: active vision by color stripes projection (MAVIS I)

volume measurement: passive vision by dual lens stereovision (MAVIS II)

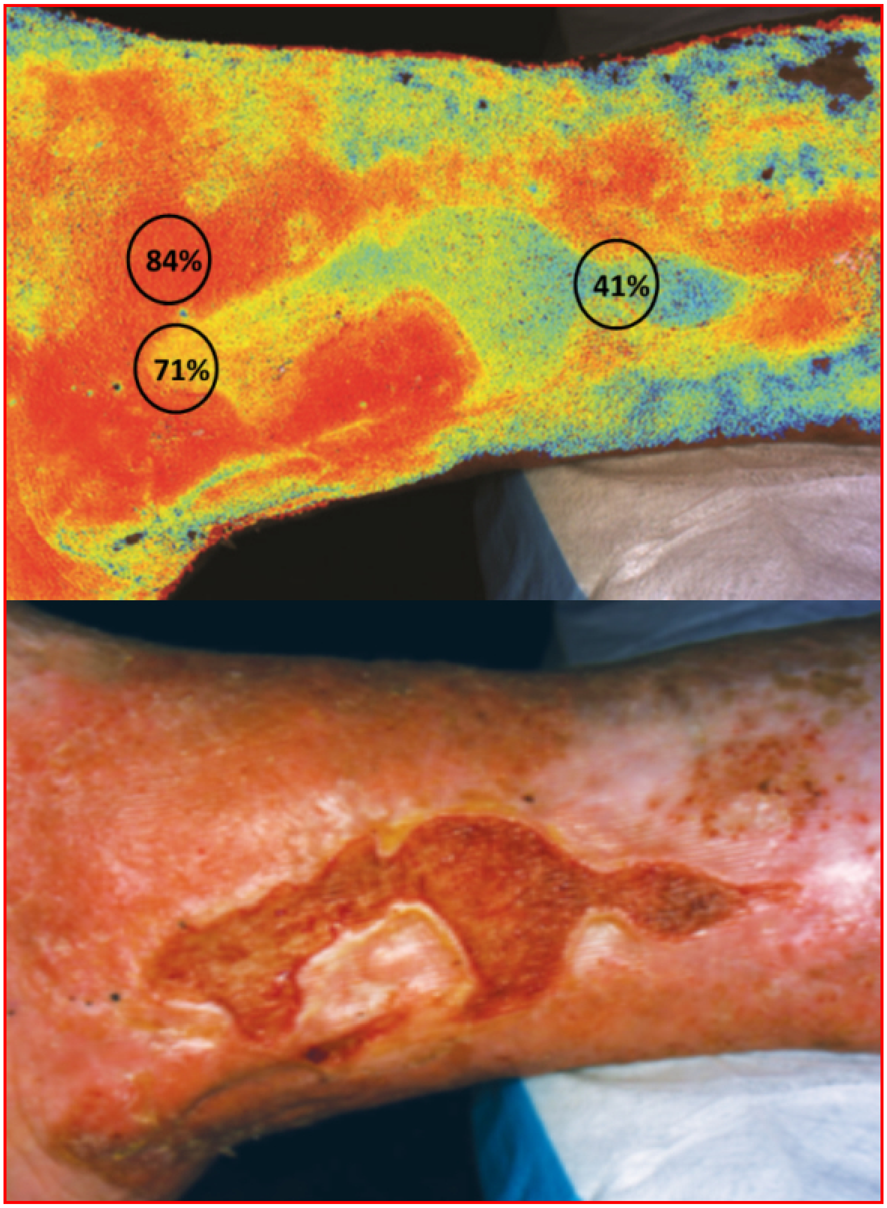


3D wound reconstruction and labelling using a simple handheld digital camera

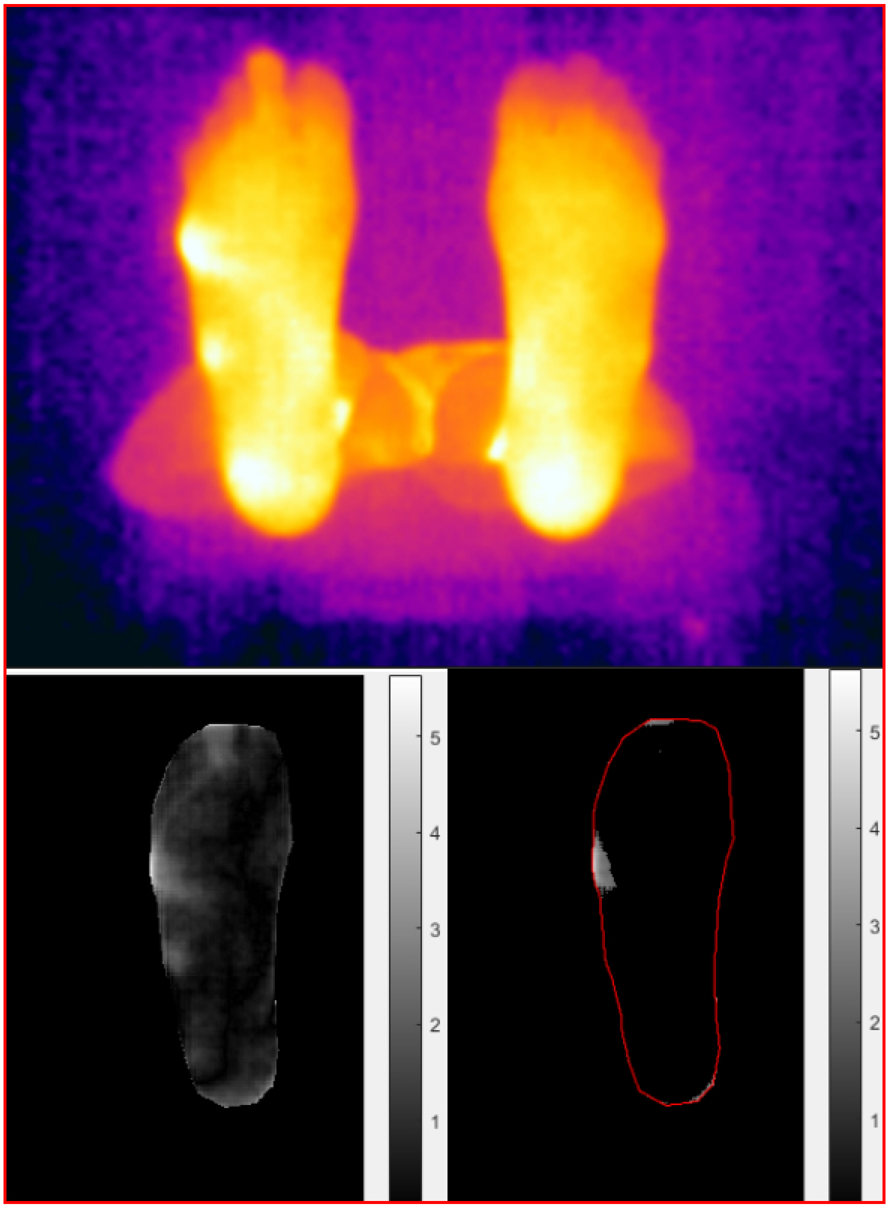
(left) Silhouette wound assessment device from Aranz medical (right) InSight device device from EKare



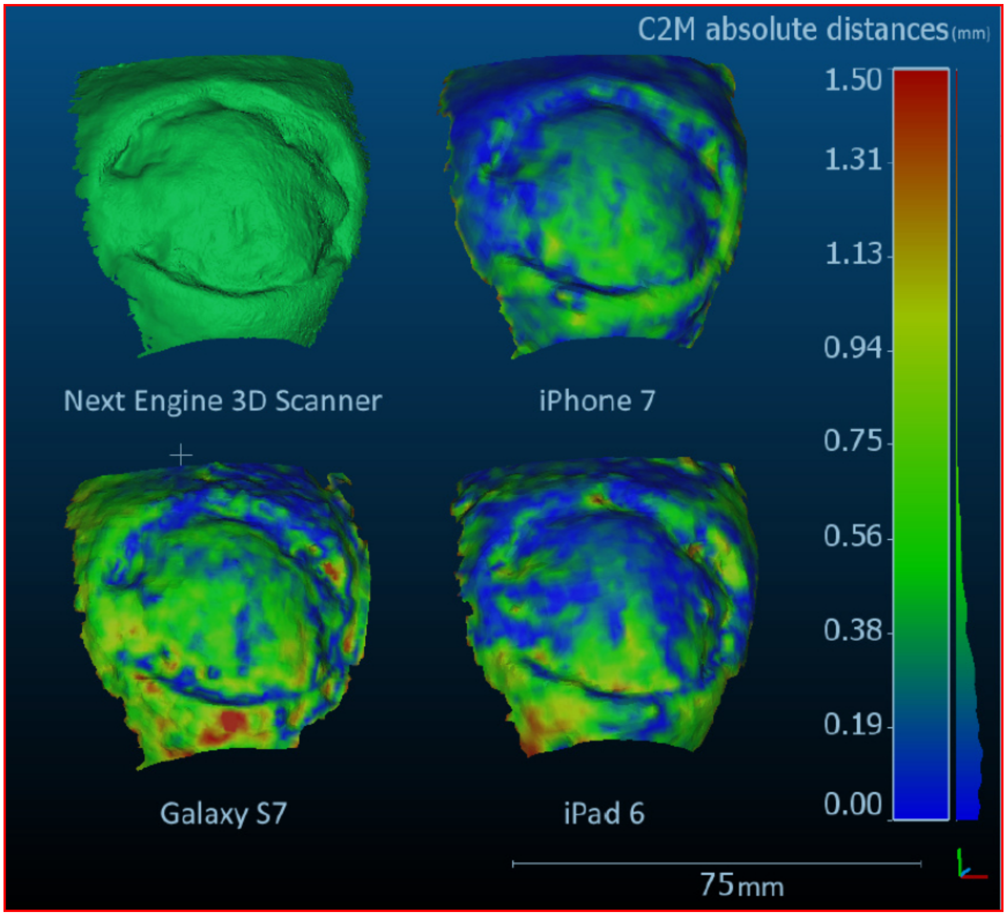
Diabetic Foot Ulcer, Heel - FL-image revealed both cyan fluorescing bacteria which is indicative of Pseudomonas aeruginosa (arrows) and red fluorescing bacteria MolecuLight i:X Wound Intelligence Device



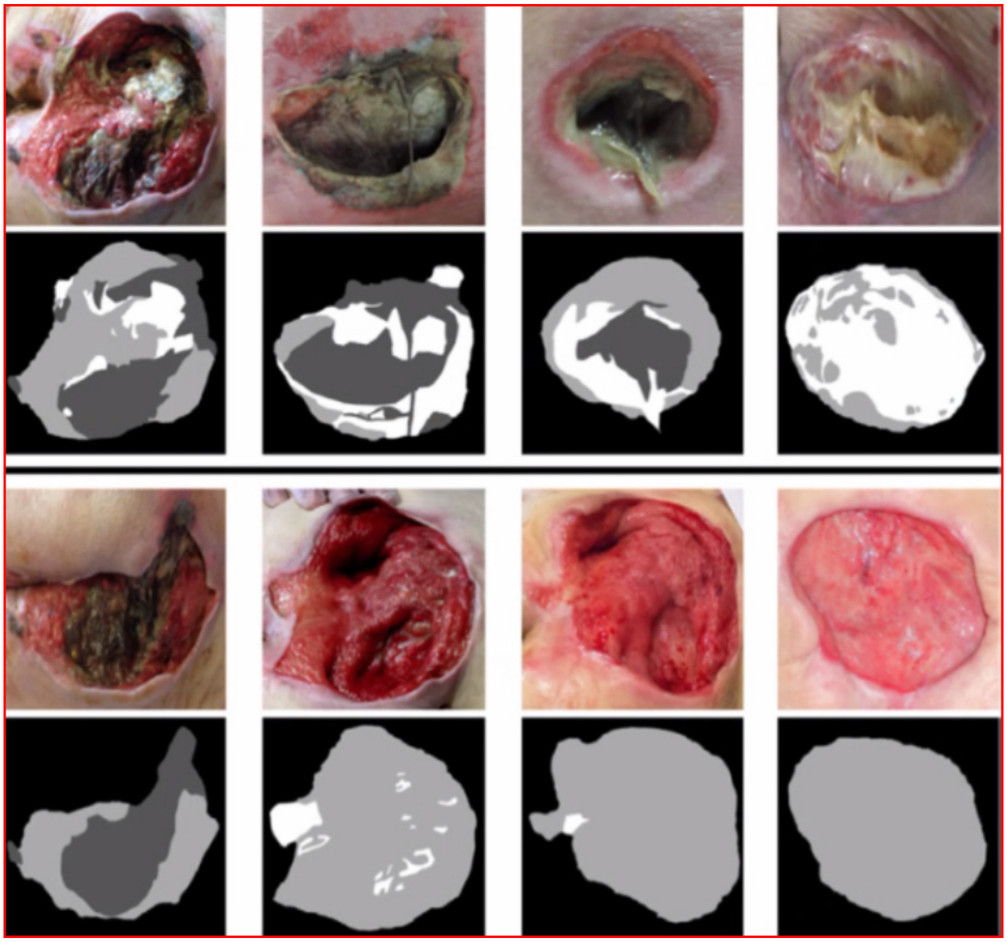
Snapshot NIR allows viewing oxygen saturation (StO2) levels throughout the wound and surrounding tissue.
Kent Imaging SnapshotNIR device



From an infrared feet image with a smartphone equipped with add-on thermal sensor (left) temperature differential can be computed (center) to detect hyperthermia for diabetic ulcer prevention (right)

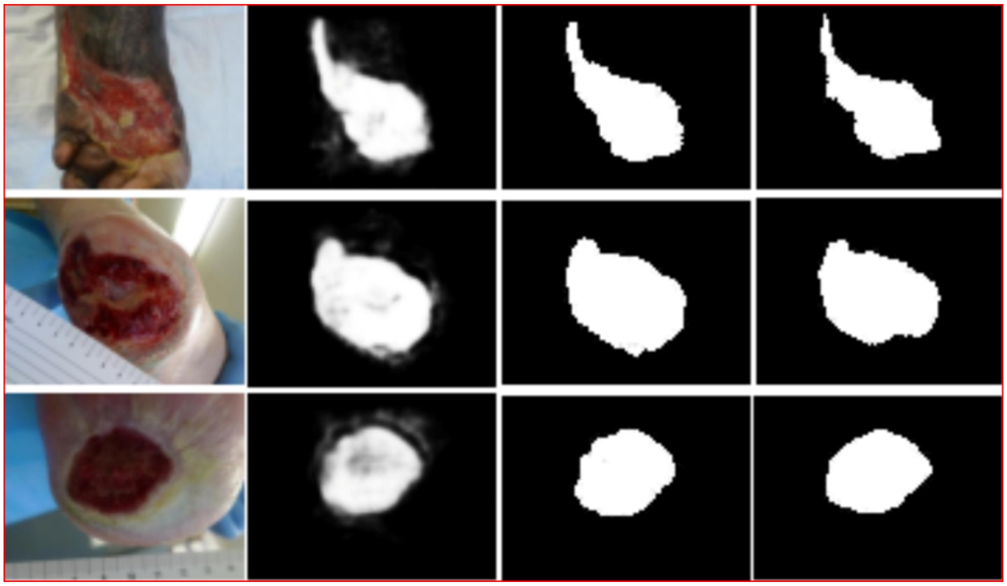


Reproducibility test: Residual distances between 3 models generated from dfferent mobile cameras after ICP registration with the laser scanner reference (top left) - Zenteno 2017



Pre-processing step for database creation (top)

and dataset dictionary for three wound tissues (bottom) - Zahia 2018



(from left to right) The cropped image is taken as input by the neural network- At the output pixel-wise probabilities of wound segment are provided in grey levels the and final mask is obtained by setting a threshold of 0.5 on every pixel, to compare with the ground truth mask displayed in the last column. Wang 2015

Structure Sensor by Occipital mounted on a tablet (top) Vivo's TOF 3D sensor for smartphone (center) Flir One PRO LT thermal camera for IPhone and IPad (bottom)

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Works	Goals	Methods	Database	Results
Sofia Zahia [2018, USA] *Tissue classification and segmentation of pressure injuries using ConvNets*	- Segmentation of the different tissue types present in pressure injuries (granulation, slough, and necrotic tissues) using a small database	- ConvNet (5 x 5 inputs)	- 22 images 1020 x 1020 - Patches 5 x5 - 75% for training set and 25% for test set	- Accuracy = 92.01% - DSC = 91.38% Precision per class: - Granulation = 97.31% - Necrotic = 96.59% - Slough = 77.90%
H. Nejati [2018, Singapore] *Fine-grained wound tissue analysis using deep neural network*	- Classification of 7 types of tissues (necrotic, slough, infected, epithelialization, healthy, unhealthy, hyper granulation)	- AlexNet (227 x 227 inputs) - SVM (HSV, LBP, HSV+LBP) - Principal component analysis	- 350 images - Patches 20 x 20 - Resizing patches to 227 x 227	3-fold cross validation: - AlexNet = 86.40% - HSV = 77.57% - LBP = 79.66% - HSV+LBP = 77.09%
Fangzhao Li [2018 , China] *A composite model of wound segmentation based on traditional methods and deep neural networks*	- Wound image segmentation framework that combines traditional digital image processing and deep learning methods	- FCN (MobileNet)	- 950 images	- Precision = 94;69%
Manu Goyal [2017, UK] *DFUNet: CNNs for DFU classification*	- Novel fast CNN architecture called DFUNet for classification of ulcers and non-ulcerous skin which outperformed GoogLeNet	- DFUNet - LeNet - AlexNet - GoogleNet	- 292 images of patient's foot with ulcer and 105 images of the healthy foot - Patches 256 x 256 - 85% for	AUC curve: - DFUNet = 0.9608 - LeNet = 0.9292 - AlexNet = 0.9504

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	and AlexNets	- SVM (LBP) - SVM (LBP+HOG) - SVM (LBP+HOG+colour descriptors)	training set, 5% for validation set and 10% testing set - Data Augmentation (rotation, flipping, color spaces)	- GoogleNet = 0.9604 - LBP = 0.9322 - LBP+HOG = 0.9308 - LBP+HOG+Colour Descriptors = 0.9430
Manu Goyal [2017, UK] *Fully convolutional networks for diabetic foot ulcer segmentation*	- Automated segmentation of DFU and its surrounding skin by using fully connected networks	- FCN-AlexNet - FCN-32s - FCN-16s - FCN-8s	- 600 DFU images and 105 healthy foot images - From 600 DFU images in the dataset, they produced 600 ROIs of DFU and 600 ROIs for surrounding skin around the DFU.	Specificity for Ulcer: - FCN-AlexNet = 0.982 - FCN-32s = 0.986 - FCN-16s = 0.986 - FCN-8s = 0.987 Specificity for Surrounding skin: - FCN-AlexNet = 0.991 - FCN-32s = 0.989 - FCN-16s = 0.994 - FCN-8s = 0.993
Changhan Wang [2015, USA] *A unified framework for automatic wound segmentation and analysis with CNN*	- Wound segmentation for surface area estimation and features extraction - Infection detection - Healing progress prediction	- ConvNet - Kernel SVM - Gaussian Process Regression	- 350 images - Patches 20 x 20 - Resizing patches to 227 x 227	Accuracy: - SVM (RGB) = 77.6% - ConvNet = 95%

Table 1 Summary of deep learning studies on wound tissue segmentation and classification