Skin temperature measurement for diagnosing leprosy in Nepal

Automatically measuring localized changes in temperature in the hand using IR-RGB thermography

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Abstract

This study investigates sensor technologies for diagnosing leprosy in Nepal, focussing on skin temperature in the hands using contact and non-contact sensors. Leprosy affects the peripheral nervous system, causing thermoregulatory dysfunction detectable via localized skin temperature changes. A systematised comparative review compares contact thermometry, infrared (IR) thermography, and IR-RGB thermography based on measurement quality, usability, and cost. Next to the systematised review, an experimental method is proposed to combine RGB and IR imaging to enhance the spatial accuracy of automatic region of interest (ROI) detection using MediaPipe Hand Landmarker. The study introduces a multimodal dataset of 45 sets of annotated IR-RGB images and validates a geometrical image registration model, achieving 93.2% keypoint detection accuracy—significantly outperforming IR-only sensors. Results show IR-RGB thermography as a cost-effective, flexible, and accurate tool for early leprosy diagnosis in resource-limited settings.

1 Introduction

A new method for early-stage leprosy detection has been developed in recent years [15; 36; 37]. It examines the hand's temperature response to cold water exposure, identifying differences in thermoregulation. Using infrared (IR) thermography, the method measures temperature variations at specific hand points, aiding in the early diagnosis of leprosy.

To ease the application of this method, there is a need to automate the extraction of temperatures at a given set of regions of interest (ROIs). One method is to use an IR thermographic camera with automatic ROI detection using MediaPipe Hand Landmarker [39; 51]. In this method the infrared images are directly used as input for the Hand Landmarker model. However, this method misidentifies about 25% of all ROIs. Therefore the accuracy is not high enough to detect ROIs reliably using this method.

In a comparative systematised review between traditional contact sensors, thermographic IR cameras and multimodal IR-RGB cameras this research compares the measurement device's quality of measurements, usability and cost for use in clinical diagnosis of leprosy in Nepal at INFs Green Pastures Hospital. We propose to use a combination of RGB and IR thermographic (IR-RGB) cameras instead of a single IR thermographic camera to increase the accuracy of automatic ROI detection.

To show the accuracy of automatic ROI detection increases when using an IR-RGB camera we have conducted an experiment along with the comparative systematised review. By (a) running the MediaPipe Hand Landmarker [51] model on the RGB image; (b) registering both images from different modalities; and (c) using the homography matrix obtained in step b to calculate the positions of the ROIs in the IR image, using the ROIs identified in step a, it is possible to detect ROIs in the IR image with high reliability.

The main contributions of this work are (1) a comparison of sensor technologies for measuring skin temperature for leprosy diagnosis in INFs Green Pastures Hospital; (2) a method for reliably detecting regions of interest on the hand in IR-RGB thermography; and (3) the creation of a multimodal dataset of 90 IR-RGB images annotated with hand landmark regions of interest.

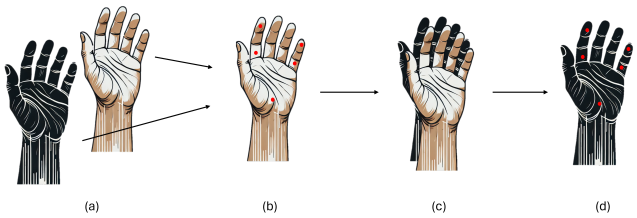

Figure 1: In our experimental method, we detect the keypoints in RGB (b), register the images in IR-RGB (c) and afterwards transform the keypoints in RGB to overlay the IR image (d). This results in an higher accuracy in detecting keypoints than in pure IR. Artist: DALL-E-2

2 Background

While Leprosy has not been around in Europe for centuries, to this day it remains a prominent disease in other parts of the world [38]. In 2019, over 200.000 new cases were reported to the World Health Organisation [7].

Leprosy develops itself mostly in the peripheral nervous system and specifically targets the lower arms, lower legs and hands [21]. Because of the affection for the peripheral nervous system, it was suggested that the detection of small deviations in the temperature regulation system, which is controlled by the autonomic peripheral nervous system, can be used to detect asymptomatic cases of leprosy before they proceed to a clinical stage [49]. The early detection of leprosy is important for adequate treatment and can limit further spreading of the disease.

To detect dysfunction in the peripheral nervous system one can use laser Doppler flowmetry to measure reduced blood flow to the fingertips. However, this technique is often too costly to apply to asymptomatic cases of leprosy. Rather, it is suggested by Abbot et al. [8] that cold fingers may be a simple clinical sign of leprosy caused by reduced blood flow to the fingertips. Cavalheiro et al. [15] show that thermography is a potential method for early detection of dysfunction of the peripheral nervous system and can therefore be used for diagnosing leprosy. While leprosy might be detectable using IR thermographic cameras, the time it takes to place correct markers of the regions of interest on the hand does make it often infeasible to do in a real world scenario.

In further research, Schemkes [39] has tried to improve the existing methods by introducing an algorithm for automatically detecting and labelling the regions of interest (ROIs) on the hands to overcome this labour intensive work. The method does automatic detection of ROIs on the hand using MediaPipe Hand Landmarker [51] directly on the IR image. This method shows issues especially in frames with higher

contrast in the IR-images caused by high temperature differences within the hands. This causes the method to be accurate in only 75% of cases, which is not robust enough to accurately detect the ROIs for temperature analysis.

3 Methodology of the systematised review on skin temperature measurement sensors

In this paper, we compare different measurement technologies that are available to measure localized changes in skin temperature in the hand for diagnosis of leprosy. This is done by means of a comparative systematised literature review with a methodology that is based on the PRISMA-guidelines [33].

3.1 Sensor selection

There are several different methods to measure the skin temperature in a clinical setting. We can broadly identify two distinct categories of temperature sensors: invasive and non-invasive temperature sensors. Invasive sensor technologies being technologies which do need to penetrate the skin of the participant to function. Non-invasive being the opposite. Non-invasive measurement devices only need to be in contact with the participant's skin to function or can even be used to measure temperature from a distance.

For this research, we consider only non-invasive methods of measurement technology because of their ease of use, their non-damaging nature and little to no requirement for hygienic measures. Within the category of non-invasive sensors, we can subdivide into contact thermometry, infrared thermometry and infrared thermography.

Contact thermometry

Contact thermometry comes in multiple different forms. The sensors used in the contact thermometry can differ in shape, size and underlying technology to measure the temperature which influence their thermal properties [30]. While there are many different sensor types we compare a simple thermistor-based sensor, because of its simplicity, low cost and wide availability. In contact thermometry for skin temperature they are often the preferred measurement method.

Infrared thermography

Infrared (IR) thermometry and infrared thermography are similar techniques. The difference is that thermometry only measures a single point. On the other hand, thermography measures an array of points forming an image of the measured subject. While thermometry is often more accurate, it lacks a good representation. Thermography on the other hand captures an image that is easily interpretable and of high resolution. Because of the need to measure multiple complex regions of interest, we will omit the IR thermometry and solely focus on the IR thermography. For our comparison we picked the Uni-T UTi721M as this is a smartphone-based IR camera that is already used in leprosy research in Nepal at INFs Green Pastures Hospital.

Infrared-RGB thermography

IR-RGB thermography is based on a hybrid camera setup which is a combination of both an IR thermographic camera and a RGB camera. While having a dual camera setup poses problems of its own, like the registration of images, the RGB image could possibly be of use in the identification of regions of interest. This could enhance the accuracy of the detected regions of interest and thus the calculated temperatures. We consider two sets of cameras. One is a conventional setup with the Uni-T UTi721M sensor and the normal phone camera side-by-side, which is relatively cheaper than a all-in-one solution, but has a need for registering the images produced in both modalities, because the images are taken from different perspectives with different cameras. The second set is a FLIR One Pro. This is a similar smartphone-based camera, which can capture IR and RGB images simultaneously with pre-aligned cameras.

This leaves us with a comparison between an array of thermistor contact sensors, the IR Uni-T thermographic camera, the hybrid Uni-T camera setup and the FLIR One Pro IR-RGB camera. All of these solutions are relatively inexpensive, widely available and are applicable for measuring skin temperature.

3.2 Criteria

To compare the different measurement technologies, we chose a set of objective criteria to compare on. In consultation with Dr. Arjan Knulst (Appendix B), who is a biomedical engineer located in Nepal and who works with the INFs Green Pastures Hospital to develop technology to detect leprosy, we decided on three criteria to compare the technologies on.

Quality of measurements

The first category is the quality of each of the measurement technologies. We identify two qualities that determine the quality of our measurements which are temperature accuracy and spatial accuracy.

Each of the sensor technologies will have specific properties that influence the measurement itself. To investigate the quality of measurements we first look at the temperature accuracy of each of the measurement technologies and the influence the sensor has on the measured skin temperature.

Next to that, it is not only necessary that we are able to measure the temperature accurately. We also need a way to accurately measure at the regions of interest. This we define as spatial accuracy.

Usability

We measure usability in three different subcategories.

The first subcategory is time spent per person and the required level of expertise to use the device in the procedure used in Nepal. In INFs Green Pastures Hospital the following procedure is used:

1. The subject is first acclimatised in a room air conditioned at 24°C,
2. After 15 minutes the subject is exposed to a cold pressure test (CPT) by putting their hands in a bucket of chilled water of 5°C,
3. After cooling the measurement of the hands start and we observe the temperatures in the following 15 minutes.

The time spent per person is most influenced by the measurement time, which is in all technologies equal. Therefore, we are here specifically looking at the setup time. Next to that, we also look into the required level of expertise to set up. If someone with no expertise can perform such a test, this would be beneficial. Also, this would be helpful if the tests are performed in the field, as stated by Dr. Knulst.

We also look into the additional needed computations to make the data of use. While contact sensors require more expertise in to set up, thermal and RGB images require more complex computations to analyse.

Finally, one of the most important points is the flexibility in measurements. As stated by Dr. Knulst, the automation of detection of ROIs on the hand supports research into, among other things, which of these ROIs are good to use. It is not determined yet which points are actually indicators for leprosy. Thus, flexibility of which points to detect is of interest for the application.

We discard hygiene as a criterion, because as stated in Dr. Knulst's response, hygiene is obtained by cleaning the contact surfaces with a sodium hypochlorite/hypochloride solution. With all technologies there are contact surfaces which do need to be cleaned.

Cost

For every technology, we compare the cost of the device and cost of the equipment needed to make the device work. We do not count the personnel costs, as this is merely a proxy of time spent and thus belongs to the usability section.

As stated in Dr. Knulst's response, cost is a great factor in the research done in Nepal. So it is beneficial if the cost of the device is kept to a minimum. A 200 euro expensive measurement device is already relatively expensive.

3.3 Paper selection

We perform a comparative systematised literature review to compare the sensor technologies on the criteria set in the previous section. The review is systematised and therefore shows many similarities to a structured review but has a more limited scope and includes not only purely scientific works but also costs and data sheets of the measurement devices that are being compared. There is no meta-analysis being performed: this review only compares the relevant sensor technologies on their qualities relevant for detecting leprosy in a clinical setting.

Search strategy

Literature is gathered through the Scopus and PubMed databases. The Scopus database is chosen for its wide variety of works in both the medical and technical domain in its collection. The PubMed database is chosen specifically for works focussed on medical application of the technologies.

The queries used are split up according to the criteria and include all sensor technologies in every query to allow for comparative literature to be taken into account. We consider query 1 for comparing the sensors on quality and query 2 for the comparison based on usability (from table 1). These were constructed with the aim of finding works that compared (a subset of) the three sensor technologies on the criteria set in the previous subsection.

For the cost comparison the approach is different. For the devices needed to run the two infrared devices, we considered the Redmi Note 12 as this is already used by Dr. Knulst in Nepal. For the thermistor sensors, we choose the a Grant Instruments thermistor. These are used in most studies reporting on skin temperature [30]. We consider that these sensors are made to work with the Squirrel sq16 logger from Grant Instruments. Even though we could consider cheaper options like creating a microprocessor based thermistor sensor logger like done by Gaspar et al. [24], this would require technical expertise which is infeasible in this context.

Inclusion of data sheets

Data sheets of the sensors are be included in the analysis to compare the intrinsic qualities of the sensors such as the accuracy of measurements. We also use the price of the devices in our comparison. For this we queried the name of the device in Google in a new window without existing cookies. We query the name of the device and looked at the first 10 results of the device, then we take the lowest price out of these ten results as the price for the device.

Inclusion and exclusion criteria

For the selected literature, we examine them by reading their title and abstract and select all relevant works using two steps. We first deduplicate the entries from Scopus and PubMed. Then we include and exclude the papers on based on their relevance.

The second step uses the following three different criteria to exclude works:

1. Non-applicable use-case: Works that are highly focussed on a certain medical domain, or don't focus on verifying the intrinsic features of their measurement devices.
2. Non-applicable sensors: Works that use different or no sensors that we aim to compare
3. Non-human application: Works that work on non-human applications for the sensors.

We use the following criteria to include works:

1. Works on the general qualities and environmental factors that influence the sensors
2. Works comparing different sensor technologies for applications in skin temperature measurement
3. Works on computational methods for processing the sensors output to extract landmarks

Justification of methodology

The PRISMA guidelines [33] are taken into consideration in the methodology of this paper. However, we do not strictly follow the protocol since it is not feasible to do this in such a short time, nor does the whole paper follow the exact structure of a systematic review due to the inclusion of an experiment. We use this method to systematically find, analyse and synthesise previous research. Scopus and PubMed supplied a set of reliable sources. The structural approach allows for repeatability and relevancy of chosen research.

Limitations

This review method has certain limitations. The databases accessed provide only a subset of the available literature, potentially excluding relevant studies. Additionally, bias may arise from the choice of keywords used for the literature search.

4 Comparison

The following sections provide an overview of each sensor under consideration. Each section highlights one of the criteria as set in the methodology for every sensor, based on information from scientific literature and technical specifications. This analysis sets the foundation for a detailed comparison in subsequent section.

4.1 Study selection

From the 235 and 196 papers that are found, in total 13 and 11 papers are selected to be included in the review. The process for both queries is shown in figure 2.

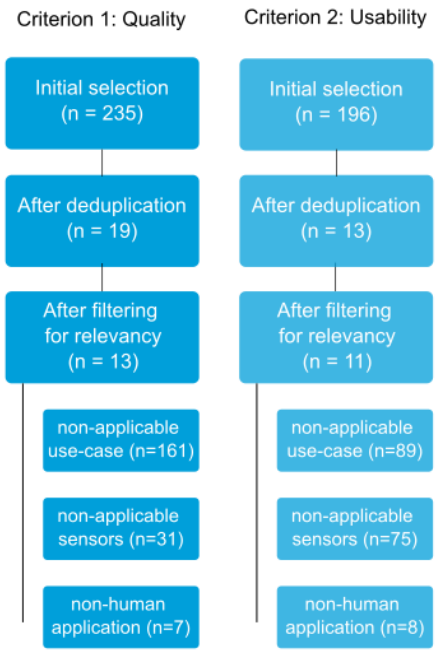

Figure 2: The paper selection process used for the literature review: Showing the process of determining the relevant papers.

4.2 Quality of measurements

In comparing the quality of measurements, we assume all sensors are correctly calibrated.

Thermistor sensors are contact sensors that have a variable resistance based on their temperature. Because of this thermistors have an accuracy normally between 0.1°C and 0.5°C, this is clinically significant [10]. Even though the thermistor is accurate in itself, there are external factors that can potentially influence the accuracy of the temperature of the object it is measuring. It is shown that incorrectly applying the thermistor with a gap between the skin or a foam pad attached to the back side decreases its accuracy of skin temperature measurements (Tsk) up to 0.6°C [12]. Furthermore, the Tsk is also significantly impacted by the method of attachment, being 'covered' or 'uncovered' in their exposure to the environment and the amount of pressure applied in the attachment [13; 31]. Compared to infrared thermography, the accuracy of a thermistor is less impacted by the temperature of the environment but it also is less responsive to change in the measured medium [9; 10; 14; 27].

Because of the method of attachment of thermistors they show good spatial accuracy, if applied by an proficient person.

In **Infrared thermography** we consider two different cameras. The Uni-T has an accuracy of 0.5°C when in 'human mode' [45]. The FLIR One Pro has an accuracy that is either ±3°C or ±5%, depending on the difference in scene and ambient temperature [43]. This means that, for the FLIR camera, the accuracy is calculated by taking 5% of the difference in ambient and scene temperature with a maximum tolerance of ±3°C. Next to that, the accuracy degrades in conditions where we measure temperature changes when rewarming from cold exposure. Infrared cameras on average report a hand temperature of about 1.80°C more than calibrated thermistors do while recovering from cold exposure [32]. Also, measured skin temperature, ambient temperature and position of the camera show an influence on the accuracy of measurements [50], which could be corrected by an error correction model specific for the IR camera used [44].

While human observers show consistent and high intrarater and interrater reliability of ROI detection in similar IR thermographic applications [40]. For computer vision models such as MediaPipe Hand Landmarker [51] several problems may arise that lead to a low reliability of around 75% correctly identified ROIs when applied to IR images.

IR-RGB thermography has the same sensor accuracy as the IR thermography, but is expected to be better in spatial accuracy when detecting the ROIs automatically since the domain where ROI are detected is the same as where the model for detecting the ROIs is trained in. In section 5 we explore a method to support this hypothesis.

4.3 Usability

Thermistors require more time to set up, due to the specific placement which should be done by someone with adequate training and experience. They are almost always less efficient than sensors that do not need to be taped [18]. The thermistor sensors also require time to settle and come to an equilibrium with the skin temperature they are measuring [24]. The settling time might interfere with the procedure since the hands are suddenly cooled in the cold pressure test (CPT). For the sensors to come to an equilibrium again might influence the measurements taken. If this technology is chosen, more research would have to be done into the impact of a cold pressure test on the measurements.

By using thermistors we are taking discrete measurements of points on the skin. This results in limited flexibility of the measurements in comparison to IR thermography. We can try to predict the temperature of a continuous part between the measured points like proposed by a computational model

for body temperature [46], computational models for calculating the mean skin temperature [19] and models based on the Finite Element Method to simulate heat flow on the skin [16]. These models do need to be adapted to predict the heat distribution in the hand. It is not known what the influence of leprosy is on the models that will be used. This would require additional research as well.

In **Infrared thermography** no extra setup time is required in the procedure. However, it has been reported that the FLIR One Pro requires 15 to 20 minutes to reach measurement stability [47]. Since the subject needs to acclimatise to the room temperature, this does not lengthen the procedural time provided that the camera is turned on on time. There is no medical expertise required from the person who will guide the procedure when using a thermographic camera.

In previous research it has been suggested to analyse the thermograms with a YOLO [11] model for detecting ROIs [28; 41] or by using automatic segmentation to distinguish hotspots from cool areas [34]. Thermography has more flexibility over thermistor based measurements as they are continuous, but rely on computational power to identify the ROIs.

For **IR-RGB thermography** the setup time is similar to the infrared camera. The difference is that the RGB camera also needs to record images. This is done automatically in case of the FLIR camera and can be enabled manually in the Uni-T camera. Again, no medical expertise is required to perform the procedure on the subject.

The IR-RGB thermograms are also continuous, making them flexible. By their nature they enable two separate domains to find ROIs in. Overlaying two separate domains either requires extra computation [42] or extra calibration [35]. Similar models like YOLO can now be run on the fused IR-RGB image to extract the ROIs with a higher reliability. We will show this method in section 5.

4.4 Cost

The cheapest option is the Uni-T UTi721M at 220 euros [5]. Together with the Redmi Note 12 at 250 euros [4] this setup is 470 euros. The difference in IR thermography and IR-RGB thermography is not of concern in these devices as the phone has enough computing power to do both tasks post-hoc.

For the FLIR One Pro the cost is 400 euros [1]. Together with the same phone we consider this worth 650 euros.

For the thermistors, the Grant Instrument thermistors costs 20 euros per thermistor [6]. We need at least 10 to track the 10 ROIs used. Next to that, we need a data logger. The Squirrel sq16 is available at £1500 [2] or 1770 euros. This makes it a total of 1970 euros.

The thermistors setup is more expensive than both the infrared cameras including the necessary devices to make them function properly.

4.5 Comparison conclusion

While costs are the highest for thermistors, they also show the most accurate results of absolute skin temperature. That is, if they are applied by a professional using the correct procedure in the right environmental conditions. On the other hand, the infrared cameras have a lower accuracy that is influenced by the environment and subject.

The spatial accuracy of thermistors is also highest due to their way of attachment. This limits the flexibility while IR and IR-RGB thermography have great flexibility in the points they measure using ROI extraction models such as MediaPipe Hand Landmarker [51] or YOLOv4 [11]. It should be noted that there exist computational models to predict skin temperature from a discrete set of points such as the thermistors measurements, but the influence of leprosy on these models is not researched. Research would also be necessary for the effect of a cold exposure on the accuracy of the thermistor sensors as this is part of the procedure in Nepal.

Due to the high price, limited flexibility and unknown effects of cold exposure on the thermistor sensors it is not recommended to employ in thermistor based contact sensors for measuring skin temperature in this procedure. Instead, we would recommend to use IR or IR-RGB thermography because of their low cost, ease of use and high flexibility. These methods do however have their weaknesses, it is advised to research the deviation in accuracy of the camera used to determine the results measured clinically relevant.

In the next section (5) we show that IR-RGB can improve the accuracy over IR thermography, while not requiring a more expensive thermal camera where the sensors are prealigned, like the FLIR One Pro.

5 Multimodal image registration

5.1 Introduction

In the systematised comparative review of this paper, several cases are identified where multimodal images in infrared-RGB have been used in a medical context to diagnose or monitor subjects.

Examples of multimodal infrared-RGB images being used in medical appliances are monitoring of newborn children [29], detection of Diabetic Foot Ulcer in diabetic patients [23] and diagnosing people with Sars-CoV-2 [22].

The amount and similarity of related cases show great potential for this method to be applied in diagnosing leprosy. In this section we explore a simple method for registration of two fixed-distance cameras in infrared and RGB based on a geometrical representation of the camera's offset. If registered correctly, the regions of interest (ROIs) identified in the RGB image can be transferred to the corresponding IR image to extract the temperature of these ROIs.

5.2 Related work

Image registration can be done in multiple ways. For multimodality like infrared-RGB, there are numerous methods developed to register the images correctly. The simplest method for aligning the images is using a geometric framework where the sensors will be physically aligned in the real world [25]. This paper will follow this approach because it is simple and applicable because of the camera sensors' fixed position.

Other methods that could potentially improve accuracy but were left out are based on neural networks, GANs or transformers [48] or using modified versions of SIFT [26]. Due to their complexity, these are not further explored in this paper.

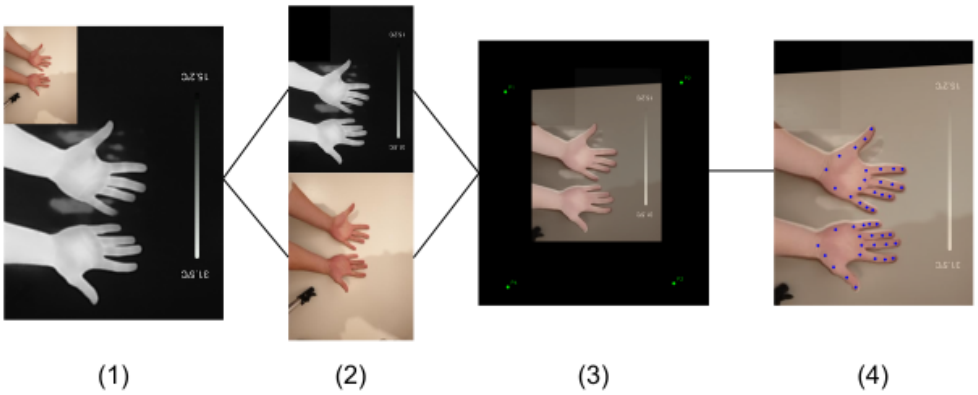

Figure 3: Dataset processing: We start with the initial image from the UNI-T app (1) and we extract both the infrared and RGB part (2). We overlay the images by hand (3) and annotate the images with the 44 ROIs (4). This set of instructions is repeated for all images in the evaluation dataset to create a dataset for evaluation of our model.

5.3 Methodology

The primary objective of this experiment is to research the possibility to extract regions of interest from the RGB image to subsequently transform these to calculate the regions of interest in the infrared image. In all cases we use Mediapipe Hand Landmarker [51] as the model to extract the ROIs because of its good accuracy in extracting regions of interest and optimisations to run on mobile devices.

Evaluation dataset

For evaluation purposes we created a dataset to compare the results of our experiments. The dataset is created using the UNI-T UTi721M camera as is used at INFs Green Pastures Hospital in Nepal. It consists of 45 pairs images in RGB and infrared. The pairs of photos were taken on a Samsung Galaxy S9+ using the UNI-T app.

We created a procedure to generate images that are hard to identify in infrared, similar to images taken from people in the leprosy research of Schemkes [39]. In this procedure, we cool the fingers one by one in a bucket of water of 5 degrees celcius and capture an image immediately afterwards. An extended explanation of the procedure can be found in appendix A.

After creation, the images were processed by three steps. First, we extract the RGB image from the combined image and fill in the space where this image used to be with a black box. In the UNI-T app, there is only a possibility to include the RGB image in the lower right corner of the image, this results in a combined image. Secondly, we align the infrared and RGB image by hand by stretching the corners until they line up. When the images are manually registered, we can calculate the homography matrix. Using the homography matrix, we can calculate the transformation we apply to the ROIs that were annotated in RGB to find the respective points in infrared. Finally, we annotate the points in RGB and obtain both the regions of interest in infrared and RGB. This process is shown visually in figure 3

Evaluation metric

Percentage of Correct Keypoints (PCK) was used to evaluate the accuracy of the methods. PCK is commonly used as a measure in evaluation of human pose prediction [17; 20; 52]. PCK is calculated by taking the true and predicted points and measuring the euclidean distance between these. If this is lower than a threshold T, the keypoint is identified as correct (eq. 1).

$$\text{PCK} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\left(\|\mathbf{p}_i - \hat{\mathbf{p}}_i\| \leq \text{threshold}\right) \tag{1}$$

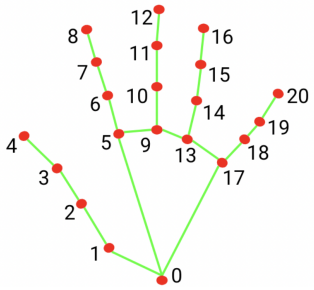

Figure 4: The threshold of PCK is determined by taking the euclidean distance between points 9 and 11, multiplied by 0.2.

The threshold is set to be the euclidean distance between point 9 and 11 (figure 4) of the annotated ground truth points multiplied by a factor 0.2. This results in a normalised threshold distance with regard to the hand size in the image [3].

Lower and upper bound

To compare the results the algorithm yields, we set a lower and upper bound to compare the accuracy of our method to. The lower bound is Mediapipe Hand Landmarker [51] executed on the infrared image set in the evaluation dataset, evaluated by the annotated evaluation data points. The upper bound is in turn set by running Mediapipe Hand Landmarker [51] on the RGB image set in the evaluation dataset, evaluated by the annotated evaluation data points.

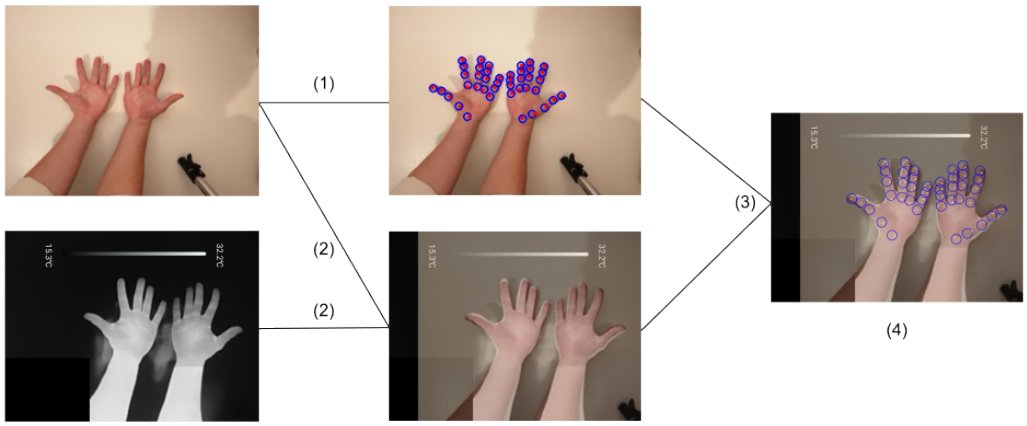

Figure 5: Image registration pipeline: We use the RGB image to calculate the regions of interest (1). We apply the image registration algorithm on both the RGB and infrared image (2). Using the output of step 1 and 2, we can calculate the points in infrared (3). This results in our final image with annotated regions of interest in infrared (4).

Mediapipe Hand Landmarker and hand orientation

While Mediapipe Hand Landmarker predicts the hand orientation, the metric it provides is not robust enough for our purposes. Since the data we provide is preprocessed to be formatted in the same way, we identify left and right hand by taking a point on the thumb and pinky and comparing their x-coordinate to determine the left or right hand. We do this for all procedures.

Image registration and keypoint detection method

The proposed pipeline consists of two parallel steps which are combined to produce the final result. The first step is the keypoint detection. The second step is the image registration. The final step is to combine the output of both steps to produce a set of keypoints identifying the regions of interest in the infrared image.

Keypoints are detected using Mediapipe Hand Landmarker in the RGB image. The accuracy is higher compared to infrared because there is no domain gap: the model is trained in the same modality as it is executed in.

Image registration is done because the images are taken from different perspectives with cameras with differing qualities. Since they only overlap partially, we have to transform one of the images so the hands overlap with the hands in the other image.

For this method we need the resolution of both images, the field-of-view (FoV) of both cameras and the offset and rotation between both cameras. If the FoV is unknown, we can calculate the FoV by measuring the height and width of the image from a fixed known distance. We can calculate the FoV using some simple geometry. We take the arctan of the height or width, divided by two times the depth. Then we multiply by two to account for both sides of the triangle formed by the camera's line of sight and the measurement depth. This gives the total angular field of view, covering the full span of the image in either the horizontal or vertical direction (eq. 2).

$$\text{FoV} = 2 \cdot \arctan\left(\frac{\text{height or width}}{2 \cdot \text{depth}}\right) \tag{2}$$

Once we have the field of view and the image resolution, we can calculate both intrinsic matrices of the cameras. The intrinsic matrix of a camera is defined as K with f_x and f_y as the resolution divided by the field of view in the respective direction and c_x and c_y as the center of the image (eq. 3).

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

We define the translation matrix T (eq. 4) with t_x and t_y as the offset divided by the depth in cm between the two cameras. We define the rotation matrix R (eq. 5) with θ as the degrees of rotation.

$$T = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$R = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

Finally, we compute the homography H (eq. 6) between the images as the intrinsic matrix K of the thermal camera multiplied by the rotation and translation matrices, multiplied again by the inverse of the intrinsic matrix of the RGB camera.

$$H = K_{\text{infrared}} \cdot R \cdot T \cdot K_{\text{RGB}}^{-1} \tag{6}$$

If we apply the homography matrix to the RGB image, we will get the corresponding image registered in infrared. In the final step of our method we use this homography matrix to calculate the detected keypoints' corresponding positions in infrared.

5.4 Experimental results

The registration and keypoint detection method proposed showed an PCK accuracy of 93.2% while the lower bound reported a PCK score of 58.6% and the upper bound resulted in a PCK score of 98.0%.

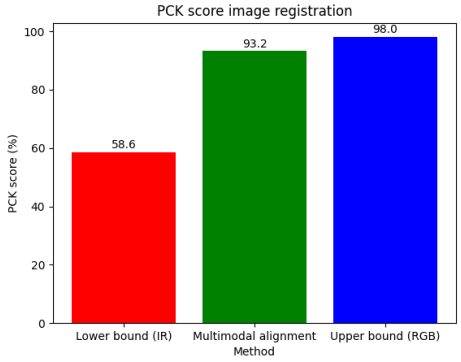

Figure 6: PCK scores of the lower and upper bound compared to the multimodal registration algorithm showing a great improvement in accuracy in the IR-RGB method.

The registration model does particularly perform better than infrared in images where hands are partly to fully cooled. In figure 7 we show some examples of low and high accuracy infrared scores with their respective infrared and registered images.

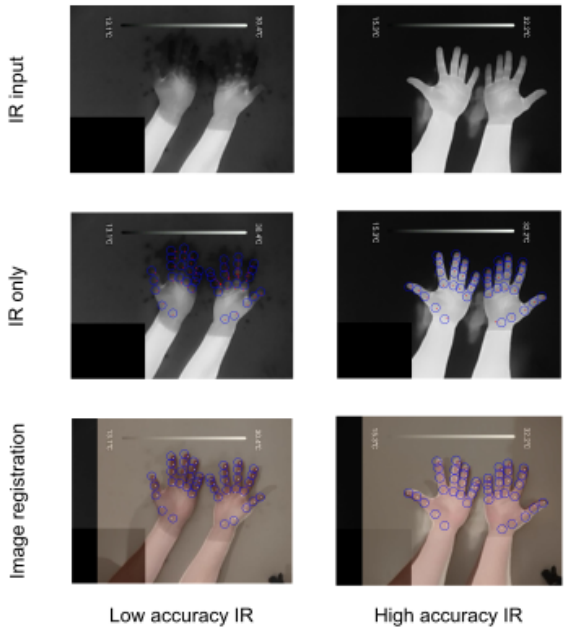

Figure 7: Examples of IR images of low and high accuracy, showcasing the cases where the the infrared hand landmark detection outputs low or high accuracy results. The IR-RGB registration method performs with high accuracy in both cases.

5.5 Discussion

In this section of the paper we explored an algorithm for detecting regions of interest on the hand in infrared-RGB while being partly cooled. The algorithm has a high accuracy in determining regions of interest in situations where Mediapipe Hand Landmarker [51] executed on single modality infrared images is not able to detect ROIs well. This makes infrared-RGB thermography especially useful in accurately detecting localized temperature changes in the skin temperature of the hand.

Limitations

The algorithm could be expanded in multiple ways to improve the accuracy of the image registration, in turn improving the accuracy of the ROI detection. With this method, the images are registered, but do not show a perfect overlap. Other image registration methods like SIFT, SURF or the use of neural networks could improve accuracy. Furthermore, the evaluation dataset used is made especially for testing the extreme cases, which do fail in infrared but does not represent the real world. We would recommend to test the algorithm on a less biased dataset to determine its accuracy in a clinical setting.

6 Responsible Research

In doing research it is important that the results are obtained in an ethically correct way. This means the work should be reproducible and choices should be well explained. Furthermore, experiment results should not be tampered with.

6.1 Comparative systematised review

In writing this comparative systematised review, the methodology is based on the PRISMA principles [33]. However, we do not strictly follow the protocol since it is not feasible to do this in such a short time, nor does the whole paper follow the exact structure of a systematic review due to the inclusion of an experiment. However, it is very important that the results can be reproduced. We have listed and motivated the sensor and criteria choice explicitly in the methodology with their respective reasoning. We have included sources like the conversations with Dr. Knulst in the appendix. Furthermore, we have described the paper selection process, with inclusion and exclusion criteria, search strategy and limitations. We believe that with this information another researcher would come to the same conclusions.

6.2 Multimodal image registration

For multimodal image registration we do not only describe the methods. The code and dataset used in the research will also be published in the TU Delft repository for other researchers to examine the results, correctness of the code and test the algorithms on their own data. Furthermore, we share the data collection setup. It has been chosen to use widely accepted evaluation metrics like Percentage of Correct Keypoints (PCK) to further transparency and make the work comparable to similar work in this field. Using the methodology and provided code and data, we believe other researchers are able to reproduce the results from this paper.

7 Discussion

This research consists of a comparative systematised review of sensor technologies to be used in diagnosis of leprosy in INFs Green Pastures Hospital in Nepal. We explore a novel way for detecting regions of interest in infrared-RGB multimodality. While the review cannot determine which sensor technology is best for this use, the combination of the review with the experiment shows that infrared-RGB is best used in Nepal. This is because of its low cost, ease of use and high flexibility while showing great spatial accuracy.

7.1 Limitations

Systematised review

The limited number of citations used in this paper reflects the niche scope of this research on sensor technologies for skin temperature measurement in leprosy diagnosis. While this approach ensures relevance in the results, it may mean that we exclude broader studies or advancements in other domains. Future reviews with a broader scope could incorporate a wider range of material to provide additional insides.

Focussed comparison

This research is highly focussed on the application of this technology in the INFs Green Pastures Hospital in Nepal. Therefore, the conclusions are influenced by input on the comparison criteria of Dr. Knulst. This influence should be taken into consideration when applying conclusions stated by this research to other situations.

Limited evaluation dataset

The dataset we now evaluate the performance on is created in a non-clinical environment using hands from healthy people. To have a better representation of the accuracy of the portrayed methods, we should diversify the set of images.

8 Conclusions and Future Work

This research investigates different sensor technologies to use in leprosy diagnosis at the INFs Green Pastures Hospital in Nepal. We compared the feasibility of using thermistor contact sensors, infrared cameras and RGB-infrared cameras for accurately measuring skin temperatures in the hands.

We conclude that infrared-RGB cameras are preferred over infrared cameras and thermistor sensors. Both infrared and infrared-RGB thermography show better performance in flexibility, ease of use and price compared to thermistor sensors.

In an experiment, we show that we can use a simple geometrical model for registration of two images in infrared-RGB. This model improves the spatial accuracy from 58.6% to 93.2% when running Mediapipe Hand Landmarker [51] over just running it on the infrared images.

Infrared-RGB thermography allows for accurate measurement of skin temperature in the hands of potential leprosy patients, aiding the diagnosis in settings where resources are limited.

8.1 Future work

We suggest that future research would focus on one of the following areas. First, the algorithm for IR-RGB registration could be more sophisticated. Where it now only includes translations and rotations, distortions and perspective changes could be added in the future to improve the accuracy of the image registration algorithm. This can be done in the geometrical model, but can also be done by making use of image registration algorithms like SIFT, SURF and techniques employing neural networks, where special attention should be given to the multimodality of the data.

Second, the variety of images and size of the evaluation dataset could be improved. The dataset does now include only a subset of potential images that can be found in practise. Expanding on this will give a more complete benchmark to measure the algorithm's performance.

Thirdly, the scope of the literature review could be broadened to explore other sensor technologies or include different categories.

Finally, more research could be done on determining the absolute and relative accuracy of the IR sensor in this procedure. It could also be determined that the absolute accuracy is not necessary for this application and that relative accuracy is sufficient.

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A Data collection setup and procedure

To collect the data the following setup was used.

A.1 Setup

The data was collected using a Samsung Galaxy S9+ using the Uni-T UTi720M camera with the UNI-T mobile application. The images were captured in image-in-image mode, with the colour scheme set to white hot and the camera in industrial mode with emissivity at 0.98. The camera was mounted using a tripod to be 64cm above the tabletop surface. The measured translation and rotation between both sensors was 12.5cm in the x-direction, 1.2cm in the y-direction and 0 degrees rotation.

Figure 8: Image capturing setup used during the dataset collection.

A.2 Procedure

The procedure was done as follows. The participant was acclimatised for 5 minutes in the room. We took photos in the following order:

1. None cooled
2. No cold finger, but hands in water for 2s (1 hand)
3. No cold finger, but hands in water for 2s (2 hands)
4. 1 finger cooled for 30s (1 hand)
5. 1 finger cooled for 30s (2 hands)
6. 2 fingers cooled for 30s (1 hand)
7. 2 fingers cooled for 30s (2 hands)
8. 3 fingers cooled for 30s (1 hand)
9. 3 fingers cooled for 30s (2 hands)
10. 4 fingers cooled for 30s (1 hand)
11. 4 fingers cooled for 30s (2 hands)
12. All fingers cooled for 30s (1 hand)
13. All fingers cooled for 30s (2 hands)
14. Whole hand cooled for 30s (1 hand)
15. Whole hand cooled for 30s (2 hands)

The hands were cooled in 5 degrees celcius cold water and the room temperature was 15 degrees celcius.

B Correspondence Arjan Knulst

From: Arjan Knulst
Sent: Friday, December 13, 2024 7:11 AM
To: Daan Posthumus
Subject: Re: Final presentation: CSE3000 - Leprosy diagnosis in Nepal

Hi Daan,
see my response in red below. [Edited as A: instead of red and made bold]
Arjan
.....
Arjan Knulst, PhD MSc
Lead Bio-Medical Engineer
INF Nepal, Green Pastures Hospital
Hariyokharka, Pokhara
9818306461

On 12/12/2024 7:58 PM, Daan Posthumus wrote:
Dear Arjan,

No problem!

I had some questions regarding my research about the application. I heard from Jan van Gemert that it was okay to send them to you. The others did not have any questions so far.

To quickly gloss over the research I am doing, the project is structured such that each of us five take a specific sub-question of the broader research. My research is focused on the question: Are IR thermographic cameras the only way of detecting temperature changes in the hand or are there better technologies available to do this.

So far, my research has been focused on doing a literature review on the different available measurement technologies for measuring skin temperatures. From this I have so far concluded that it might be better to use a combined thermal IR and RGB camera (such as the FLIR One Pro) because this allows for easy hand detection in RGB (existing models are trained quite well for this), while still allowing for accurate temperature measurements in IR. Next to that, I am also investigating if I can create an algorithm to overlay/align the images taken by the Uni-T IR camera you already use onto an RGB image taken by another phone, to allow you to keep costs down while still benefitting from the advantages of blending IR-RGB technology. Next to exploring the IR-RGB hybrid cameras I also investigated more traditional approaches such as contact temperature sensors.

The comparison of the three technologies is based on three criteria: cost, accuracy, and usability. I really want to get a feel for the situation you are working in to make the comparison as useful as possible. Therefore, I came up with the following questions:
1. Is the cold pressor test done (as described by Irene Schemkens) because it broadens the contrast in temperature as opposed to a cold stress on the palm as proposed in the original work of Cavalheiro et al.?
A: Cold stress on the palm using cold spray did not work well for us. Very uneven cooling, and only superficial, so a very quick recovery as the hand itself is not cold, just the top layer of the skin.
2. How significant should the detected temperature differences be for you to detect if someone has leprosy?
A: That's what we hope to see in our research. Not much is known yet about what to expect.
3. Is spending a couple hundred euros more on a measurement device realistic for the situation in Nepal? Or should extra cost be minimized?
A: I would try to avoid spending more money, this is already relatively expensive.
4. What takes the most time in the setup, measurement, and analysis of skin temperature, in the current setup? What should be minimized to up the efficiency of this process?
A: The measurement itself takes most time.
5. Is there an obvious reason for you not to work with contact sensors, such as thermistors you just tape to the skin?
A: It all started with the idea to see the whole hands and make comparisons, see if some locations would respond differently. In the research we take few selected locations which are most prone to see deviations, but we could take different locations later. Any automated analysis could even give more points of interest. The outcome is also very visual with IR image on screen. Taped thermistors would maybe have an issue with submerging in water.
6. Is the appliance only to be used in the hospital or also for patients at home?

A: If the whole process is useful for diagnostics it could be a field test for screening purposes (hence a setup to fixate the hands is not very practical, an automated approach would allow to track hands while moving or changing position. The setup is just to fixate the hands as our current analysis method relies on clicking fixed locations that are assumed to be stable throughout the video..

7. How much of a concern is hygiene, since the transfer of leprosy only happens due to long term contacts, I would suppose this is of little concern?

A: Our current setup is cleaned using a sodium hypochlorite/hypochloride solution. Common for surface disinfection in hospitals. It is believed to be sufficient to prevent cross-contamination.

Thanks in advance for your response, if there is anything significant you like to add, please do so!

Kind regards,

Daan Posthumus

C Search queries

No.	Query	No. Results (Scopus + PubMed)
1	(("thermistor*") OR ("infrared camera" OR "IR camera" OR "infrared thermo*")) AND "skin temperature" AND "human" AND "measure*" AND (quality OR accuracy OR sensitivity OR reliability)	206 + 27
2	(("clinical setting*" OR "medical") AND "temperature measurement" AND "method*" AND "skin temperature")	152 + 44

Table 1: Search queries from the comparative systematised review