Digital Human Modeling and Applied Optimization, Vol. 46, 2022, 25–34
https://doi.org/10.54941/ahfe1001896

Methodology Based on 3D Thermal Scanner and AI Integration to Model Comfort and Ergonomics

Consuelo Latorre-Sánchez, Juan Antonio Solves-Llorens, Joaquín Sanchiz-Navarro, Ricardo Bayona Salvador, José Laparra-Hernández, Nicolas Palomares Olivares, and José Solaz Sanahuja

Institute of Biomechanics of Valencia, Valencia, Spain

ABSTRACT

Thermal comfort depends on many physical parameters, from air temperature to body temperature regulation, through gender, age, clothing and other general and local characteristics of the body. Analyzing **body's thermoregulatory response** and measuring surface temperatures and their evolution, a methodology has been created, allowing to relate differences in thermal maps, to pathologies, skin affections or joint injuries. With a low-cost, near real-time system and contactless technology, using 3D thermal imaging and artificial intelligence, Health and Wellness applications have been set up to help physicians diagnose certain diseases, such as circulatory and vascular problems and the effect of therapies or cosmetic products. From a huge Infrared database (>300 k), models have been trained to estimate sex, age, **thermotype** and user identification. These algorithms improve the **Thermal Digital Human Model** derived from thermography, questionnaires and databases of body shapes (3D scans), and permit predict **user's features**, **thermal comfort** and **thermal behavior**.

Keywords: Human model, AI, Thermal image, 3D reconstruction, Infrared, Depth sensors, Face recognition, Thermotype, Facemasks, Thermal scanner, Thermoregulatory

INTRODUCTION

The aim of this study is to use the power of thermography to **understand human behavior**, applying very promising techniques of artificial vision and 3D reconstruction, to obtain information from thermal images about the user, features and propose a follow-up of treatments, help to diagnose or predict thermal sensation and thermal comfort.

Thermal comfort is a subjective psychological perception. It is defined as that condition of mind which expresses satisfaction with the thermal environment (i.e., with the combined effect of air temperature, humidity, wind speed, and thermal radiation) and it is assessed by subjective evaluation (American Society of Heating, 2004). No thermal environment can satisfy everybody (Fanger, 1970), and individual differences, sex, age, nationality and other parameters have an effects on the subjective perception of the thermal comfort. Reviewing the scientific literature, gender, age, nationality differences in thermal comfort are considered to be small and insignificant (Fanger, 1970; Humphreys, 1976) at neutral temperatures. However, **recent published studies reveal significant differences between genders** (Djongyang et al., 2010; Frontczak and Wargocki, 2011; van Hoof, 2008).

Moreover, without distinction for the sex variable, **the perception of thermal comfort worsens with age**.

Above neutrality, people regulate body temperature by vasodilatation and sweating. Sweat rates and sweat distribution are different in gender, age and thermotypes (Latorre-Sánchez et al., 2020). Sweat is distributed in females more heavily towards the lower body than males. (Smith and Havenith, 2012, 2011). When the body cools down, the first reaction to heat production is **vasoconstriction,** reducing blood flow through the skin, and increasing internal heat production by stimulating the muscles.

In presence of pathologies or injuries in skin, joints or muscles, the body's thermoregulatory response presents localized and/or generalized changes. Acute and chronic pain can be a difficult medical problem to diagnose and treat and can be caused by symptoms such as tissue injury, inflammation, a surgical procedure, or disease. On many occasions the pain is associated with a **variation in local temperature**. Skin pathologies also show variations in the thermal pattern of a subject. For this reason, InfraRed Images (IR) provide additional and complementary information.

The current pandemic situation due to the appearance of the coronavirus-2 or SARS-CoV-2 (COVID-19) has increased the demand and familiarization of the population with infrared cameras and their thermal interpretation. The Institute of Biomechanics of Valencia (IBV) has integrated thermal information to applications based on anthropometric scanners, allowing to combine shape, posture, movement and temperature variations. Thermography is a non-invasive, non-radiating technique particularly valuable for the exploration of the topography or pattern of skin temperature across the body (Fournet, D., 2013; James C et al., n.d.). Medical infrared thermography is used for analyzing physiological functions related to skin temperature. Technological advances have made it a reliable medical measurement tool (Hildebrandt et al., 2010).

Artificial Intelligence (AI) techniques applied to images, mainly in visible or RGB datasets, have undergone significant development in recent years, however there is a **gap in the application in thermal images.** The IBV has compiled a powerful database for years from many users, insulation in clothes, extreme scenarios and different poses and face orientations.

Many networks, models and libraries of computer vision, have been explored and some AI techniques (Machine Learning and Deep Learning) have been applied to extract information from those images, although open solutions and networks do not work accurately. The thermal database has been used to retrain these network models and the results have been considerably better, being able to **detect body silhouettes**, **faces**, **recognition** and **predict user's characteristics** such as age, gender or thermotype and achieve Thermal Comfort predictions useful to design intelligent self-adjustable

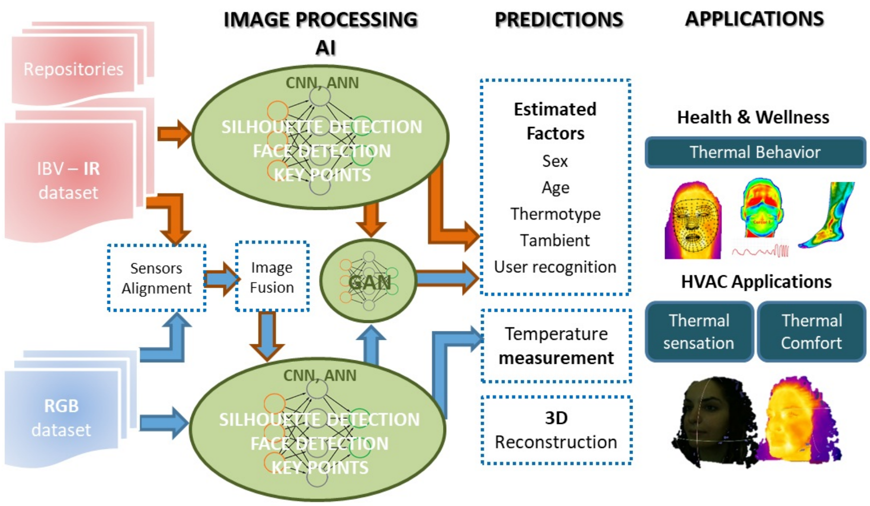

Figure 1: Scheme of the study: Global approach.

thermal systems. Algorithms that identify the subject and automatically measure the temperature at predefined key points, also allow to track changes in the temperature of parts of the body and generate a multitude of Health applications.

METHODS

The methodology of this study of IR image processing began performing Image Fusion between visible and infrared images form a synchronized dataset in order to extrapolate feature extraction and key points from visible images to thermal ones.

The second part was testing AI techniques used for visible or RGB images on IR dataset. (See Fig.1). **Silhouette or face detection models were retrained with the thermal dataset, and key points were used to measure the temperature automatically.**

Finally, these techniques were applied to 3D thermal scanner, with a low-cost, near real time system that integrates visible and thermal information in different layers.

Within the IVACE TERMO4D project, innovative methodologies based on IR have been implemented applying AI techniques in a database from a wide range of cameras, from high-cost and precision systems for laboratory (< 0.02K) to low-cost solutions. This user database is made up of more than 300k thermographs and thermal sequences, in a temperature range from −5°C to + 40°C, with different clothing and postures. The dataset of this study is composed for IR images, NIR (Near IR) images and visible RGB (Red-Green-Blue) images from thermal cameras FLIR T650sc, FLIR A35, OPTRIX and the depth sensor Intel RealSense (Table 1). Open repositories have been also used (Nikisins et al., 2014).

Table 1. Camera, resolution, numbers of images, example

Camera	Images	Format	Resolution pixels	Images per user	N° users	N° images
FLIR T650sc	RGB & IR	*.jpeg	640x480 2592x1944	90	70	6500
FLIR T650sc	RGB	*.csq	640x480	18000	10	180000
FLIR A35	IR	*.yml, *.gz	320x240	140	30	4200
OPTRIX	IR	*.yml, *.gz	382x288	random	150	>5000
Intel Real Sense D435	RGB & NIR	*.png	1280x720	40	30	1200

AI Applied on RGB Images and Extrapolation to IR

Applying AI techniques to **data conditioning** was the first objective. Images and videos from FLIR T650sc dataset are encoded and must be converted before any usage. This camera provides IR images and RGB at simultaneous trigger.

In order to use the RGB-Thermal pairs, a transformation matrix was developed to compensate the misalignment between the RGB and the thermal collections.

The preliminary approach was to perform data extraction from RGB images and extrapolate it to the thermal images. This result provides very good results although it is limited to datasets with synchronized RGB and thermal images.

Detection problems have become one of the most important tasks in artificial vision scenarios, and mainly **face detection**. The Viola-Jones algorithm (Viola and Jones, 2001) and the YOLO (You Only Look Once) algorithm (Redmon et al., 2016) were selected. V&J is characterized by being robust, in real time, based on classical techniques and only for grayscale facial recognition problems. In modern computer vision detection problems, robustness is one of the most important aspects to consider, as well as speed of inference. YOLO arose from mixing these two features, applying a single Convolutional Neural Network (CNN) to the entire image.

The problem of **facial recognition** has been extensively studied. Classical algorithms have been proposed to solve this problem (Albiol et al., 2008; Heisele et al., 2001; Hildebrandt et al., 2010) and more recently, deep learning approaches can achieve human-like performance in person recognition (Schroff et al., n.d.; Sun et al., 2015; Taigman et al., 2014). Those approaches use CNNs to derive feature vectors that are capable of identifying faces. Other solutions are based on **landmarks.** Keypoints have also been applied in an RGB body landmark convolutional model (SimplePose (Li et al., 2020)) and with Mediapipe libraries (Lugaresi et al., 2019).

Points have been extracted using these models in the RGB dataset and overlaid with their corresponding thermal image. Several thermographs of

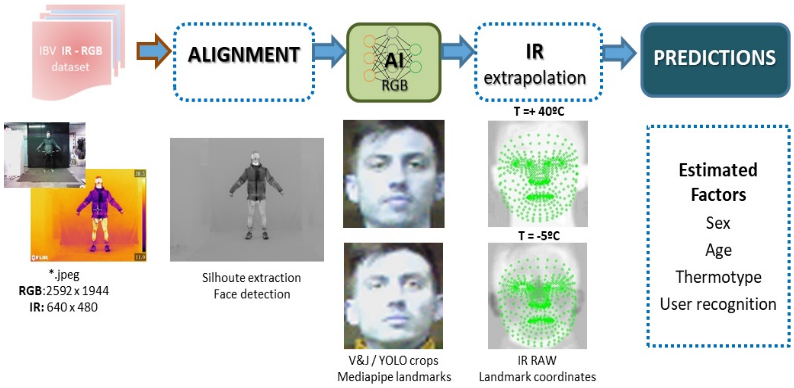

Figure 2: AI applied on RGB dataset and Mediapipe extrapolation to IR images.

each user were used at different ambient temperatures to estimate factors such as the user's thermotype.

AI Applied on IR Images

Focusing on the use of thermal imaging, algorithms were tested. PSPNet, ViolaJones or YOLO have been retrained with full body thermal data from FLIR T650sc and FLIR A35 cameras.

First step has been to **detect the silhouette** from IR images. For the segmentation of the human body in thermal images, a PSPNet (Zhao et al., 2017) with thermal images has been retrained to recognize two classes: human body and background. Second step has been to **detect faces** on IR images. Some Viola-Jones models and YOLO have been trained. Positive and negative samples have been extracted from **VAP RGB-D-T Facial Database** (Nikisins et al., 2014) using face bounding boxes for positive samples, and other parts of the image as negative samples. YOLO has been selected as a solution for the big number of false positives produced by Viola-Jones algorithm.

Over the detected faces, two methods have been considered for **user recognition** and **soft biometric traits estimation.**

- Method I: based on using IN images as normal images to obtain **feature vectors that identify faces** from different people. Some studies used CNNs trained in normal images (Kakarwal et al., 2020; Mostafa et al., 2013) and others retrained popular CNNs with thermal images (Kakarwal et al., 2020; Szankin et al., 2019). In this study a known CNN for image classification has been used: VGG16 (Simonyan and Zisserman, 2015), pretrained with the public dataset ImageNet (Russakovsky et al., 2015). Soft biometric traits from facial images has been estimated using feature vectors obtained from CNNs to directly guess biometric traits (Kurbanov et al., 2019; Qawaqneh et al., 2017). The feature vectors from the modified VGG16 (used in facial identification) had been used for **gender, age** and **thermotype** estimation. A simple Feed-Forward Neural Network (FFN) and a Support Vector Machine (SVM) were utilized to obtain those biometric traits, applying also a Principal Component Analysis (PCA) reduction to **reduce the size of feature vectors** and to **short training time**.

- Method II: based on key points. The thermal measurement information at the located reference points is used to obtain data such as **thermotype**, **age** or **gender**. A RGB body landmark convolutional model (SimplePose (Li et al., 2020)) was preliminary retrained to detect facial landmarks. For the thermal face landmark dataset, some concrete point locations to measure the temperature were selected from Mediapipe (Lugaresi et al., 2019). An algorithm based on the probability of appearance, following a gaussian distribution, has been generated to reduce the number of landmarks from 468 to 12.

The study of artifacts in the thermal faces like beard or glasses, has made it possible to explore new lines of study such as the detection of the respiratory rate in facemasks or the presence or absence of certain personal protective equipment (PPE).

RESULTS AND DISCUSSION

A modular equipment has been developed with embedded software to facilitate the protocol and methodology with several thermal cameras. Multiple systems have been installed in collaborating companies and some selected examples of end applications derived from this study are listed below:

Human Detection and Face Recognition

The detection of the human body, gender, sex and user recognition have been estimated through IR images and through thermal information at selected reference points (landmarks).

Concerning to **face detection**, 23.000 images of 640x640 from the repository (Nikisins et al., 2014) have been trained and its corresponding facial bounding box in batches of 64 images for over 300 epochs. **Data Augmentation** such as horizontal flip, random rotation and zoom has been used in order to give the model more generalization. SGD optimizer and a learning rate of 0.001 have been used to train the model. For **user recognition**, 637 thermal images from 45 different users, were used for training, and 52 thermals from 4 unknown different users. The same number of images and characteristics was used in **biometric traits estimation**.

One of the purposes of obtaining these factors is to be able to estimate ambient temperature and predict thermal sensation and thermal comfort in any scenario.

Facemask Detection Fitting on and Breathing Rate Estimation

From infrared videos, the breathing rate could be estimate due to the range of temperatures between inhalation and exhalation is greater than ambient temperature at neutral conditions. An algorithm to estimate the **respiratory frequency** and **fitting on the facemask**, has been developed measuring the temperature on facemasks and around the face. For each thermal sequence the face and facemask have been detected with YOLO 5s (Ding et al., 2021)

Figure 3: YOLO and Viola&Jones crops and mediapipe 468 landmarks on IR images with rotations and facial expresions. FLIR A35.

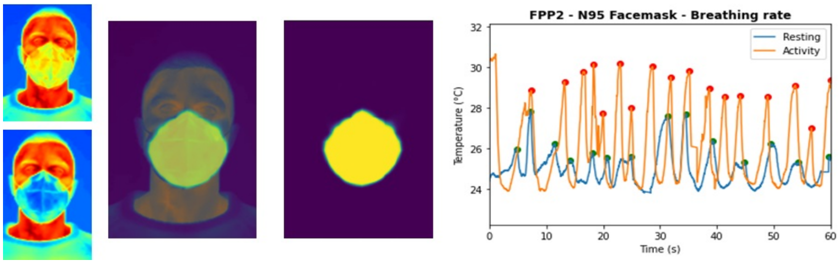

Figure 4: Inhalation and exhalation detection through FFP2-N95 facemasks.

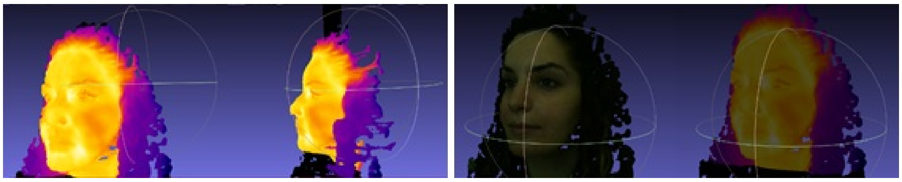

Figure 5: 3D reconstruction.

version and the temperature values of a central ROI have been extracted. Detecting the peaks of the temperature signal, period, mean, minimum and maximum breath durations, the breath rates are measured.

This methodology permits to compare between different **sizes** and **shapes** of facemasks according to anthropometrics characteristics of the user and also evaluate the resistance to the breathing of different materials.

RGB-IR 3D Reconstruction

The combination of 2D and 3D thermal and anthropometric information and Artificial Vision techniques has allowed real-time 3D reconstruction of an area of the body, with a simple and low-cost system, made up of a thermal artificial vision camera and a low-cost depth sensor (Intel RealSense 435). Two cameras were fixedly arranged and their spatial relationship was obtained by geometric calibration (calibration target) based on the pinhole camera model. (Rangel and Soldan, 2014).

The integration of AI algorithms for face and feature recognition and temperature measurement with visible images has led to an improvement in 3D reconstruction.

A complete representation is obtained, where thermal, visual and depth information can be selected.

CONCLUSION

In the post-pandemic world, commercial solutions to existing problems with infrared technology are being developed from efficient approaches. Artificial intelligence in medical imaging has gone mainstream in recent years. The application of AI in infrared thermography and automatic real-time temperature measurement implies updating an already known technique with new solutions. **Face identification, gender, age**, and **thermotype** estimation were extracted from IR images by retraining RGB networks **without the need to label or mask an IR dataset beforehand**. AI algorithms to extract key points allow to measure temperature changes in the body and analyze the body's thermoregulatory response. The thermal video sequences provide information on breathing under neutral conditions and distinguish temperature changes due to inhalation from exhalation.

It has also been possible to unify the thermal information of the infrared images with 2D and 3D anthropometric information with a low-cost, real-time system. This unification allows the future development of applications to evaluate the user-product interaction and the characterization of pathologies in patients by merging RGB and visible.

These results enhance the Digital Human Model, providing it with useful information for many applications.

Future Lines

Improve detection and thermal facial recognition, detecting and correcting turns and rotations of faces. An important line to explore is the influence of emotions, ambient temperature or effort/activity on facial recognition and thermal patterns.

It is also exploring how to identify the person in the presence of PPE (Personal Protection Equipment) such as a mask, goggles or a helmet, including detecting and removing them.

Finally, the automatic detection and measurement of temperature in motion (MOVE 4D) is the main milestone, for the monitoring of injuries, detection of pathologies or thermal behavior with different garments and activities.

ACKNOWLEDGMENT

This research activity has been supported by Instituto Valenciano de Competitividad Empresarial (IVACE): Project "TERMO4D" (IMDEEA/2022/48), within the framework of the program of grants directed to Technological Centers of the Valencian Community for the development of non-econocmic R&D projects for the financial year 2022, co-funded by European Union and the Project "IBV 2022 R&D activities plan" ((IMAMCA/2022/7) funded by IVACE and Valencian Regional Government (GVA) funding.

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