Thermal Cameras and Applications

A Survey

Gade, Rikke; Moeslund, Thomas B.

Published in:
Machine Vision & Applications

DOI (link to publication from Publisher):
10.1007/s00138-013-0570-5

Publication date:
2014

Document Version
Accepted author manuscript, peer reviewed version

Machine Vision and Applications (2014) 25:245-262
DOI 10.1007/s00138-013-0570-5

Thermal Cameras and Applications: A Survey

Rikke Gade · Thomas B. Moeslund

Received: 13 August 2012 / Revised: 24 July 2013 / Accepted: 15 October 2013

Abstract Thermal cameras are passive sensors that capture the infrared radiation emitted by all objects with a temperature above absolute zero. This type of camera was originally developed as a surveillance and night vision tool for the military, but recently the price has dropped, significantly opening up a broader field of applications. Deploying this type of sensor in vision systems eliminates the illumination problems of normal greyscale and RGB cameras.

This survey provides an overview of the current applications of thermal cameras. Applications include animals, agriculture, buildings, gas detection, industrial, and military applications, as well as detection, tracking, and recognition of humans. Moreover, this survey describes the nature of thermal radiation and the technology of thermal cameras.

Keywords Thermal camera · Infrared radiation · Thermal Imaging · Computer Vision

1 Introduction

During the last couple of decades, research and development in automatic vision systems has been rapidly growing. Visual cameras, capturing visible light in greyscale or RGB images, have been the standard imaging device. There are, however, some disadvantages to use these cameras. The colours and visibility of the objects depend on an energy source, such as the sun or artificial lighting. The main challenges are therefore that the images depend on the illumination, with changing intensity, colour balance, direction, etc. Furthermore, nothing can be captured in total darkness. To overcome some of these limitations and add further information to the image of the scene, other sensors have been introduced in vision systems. These sensors include 3D sensors [124, 126, 144] and near infrared sensors [170]. Some of the devices are active scanners that emit radiation, and detect the reflection of the radiation from an object. Night vision devices, for example, use active infrared cameras, which illuminate the scene with near infrared radiation (0.7–1.4 μm) and capture the radiation of both the visible and the near infrared electromagnetic spectrum. Such active sensors are less dependent on the illumination. Stereo vision cameras are passive 3D sensors, but as they consist of visual cameras, they also depend on the illumination.

The described sensors indicate that some of the disadvantages of visual cameras can be eliminated by using active sensoring. However, in many applications, a passive sensor is preferred. In the mid- and long-wavelength infrared spectrum (3–14 μm), radiation is emitted by the objects themselves, with a dominating wavelength and intensity depending on the temperature. Thereby they do not depend on any external energy source. Thermal cameras utilise this property and measure the radiation in parts of this spectrum. Figure 1 shows an example of the same scene captured with both a visual and a thermal camera. The thermal image is shown as a greyscale image, with bright pixels for hot objects. The humans are much easier to distinguish in the thermal image, while the colours and inanimate objects, like chairs and tables, are invisible.

A special detector technology is required to capture thermal infrared radiation. Originally it was developed for night vision purposes for the military, and the devices were very expensive. The technology was

R. Gade · T. B. Moeslund
Visual Analysis of People Lab, Aalborg University
Aalborg, Denmark
Tel.: +45 9940 7124
E-mail: rg@create.aau.dk

Fig. 1 Visible and thermal image of the same scene.

later commercialised and has developed quickly over the last few decades, resulting in both better and cheaper cameras. This has opened a broader market, and the technology is now being introduced to a wide range of different applications, such as building inspection, gas detection, industrial appliances, medical science, veterinary medicine, agriculture, fire detection, and surveillance. This wide span of applications in many different scientific fields makes it hard to get an overview. This paper aims at providing exactly such an overview and in addition provides an overview of the physics behind the technology.

The remaining part of this survey consists of the following sections: Section 2 describes the physics of thermal radiation and Section 3 explains the technology of the cameras. Description of the application areas and a survey of the work done in the different areas are found in Section 4. In Section 5 it is discussed how to fuse the thermal images with other image modalities, and the application areas for fused systems are surveyed. Finally, Section 6 summarizes and discusses the use of thermal cameras.

2 Thermal Radiation

Infrared radiation is emitted by all objects with a temperature above absolute zero. This is often referred to as thermal radiation. This section will go through the source and characteristics of this type of radiation.

2.1 Electromagnetic Spectrum

Infrared radiation lies between visible light and microwaves within the wavelength spectrum of 0.7–1000 μm as illustrated in Figure 2. The infrared spectrum can be divided into several spectral regions. There exist different sub-division schemes in different scientific fields, but a common scheme is shown in Table 1 [24]. The mid-wavelength and long-wavelength infrared are often referred to as thermal infrared (TIR) since objects in the temperature range from approximately 190 K to 1000 K emit radiation in this spectral range.

Division Name	**Abbreviation**	**Wavelength**
Near-infrared	NIR	0.7–1.4 μm
Short-wavelength infrared	SWIR	1.4–3 μm
Mid-wavelength infrared	MWIR	3–8 μm
Long-wavelength infrared	LWIR	8–15 μm
Far-infrared	FIR	15–1000 μm

Table 1 Infrared sub-division.

The atmosphere only transmit radiation with certain wavelengths, due to the absorption of other wavelengths in the molecules of the atmosphere. CO_2 and H_2O are responsible for most of the absorption of infrared radiation [181]. Figure 3 illustrates the percentage of transmitted radiation depending on the wavelength, and states the molecule that is responsible for the large transmission gaps.

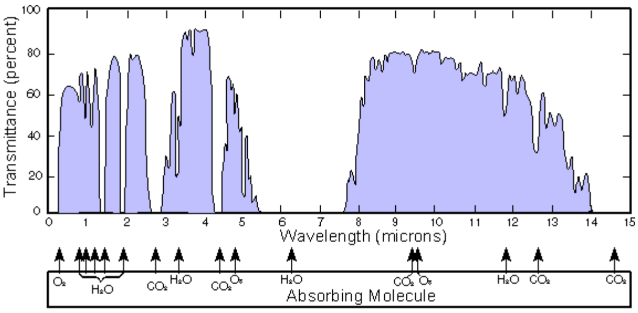

Fig. 3 Atmospheric transmittance in part of the infrared region [187].

Due to the large atmospheric transmission gap between 5–8 μm, there is no reason for cameras to be sensitive in this band. The same goes for radiation above 14 μm. A typical spectral range division for near-infrared and thermal cameras is shown in Table 2.

Division Name	**Abbreviation**	**Wavelength**
Short-wave	SWIR	0.7–1.4 μm
Mid-wave	MWIR	3–5 μm
Long-wave	LWIR	8–14 μm

Table 2 Infrared sub-division for cameras.

2.2 Emission and Absorption of Infrared Radiation

The radiation caused by the temperature T of an object is described by Planck's wavelength distribution function [159]:

$$I(\lambda, T) = \frac{2\pi hc^2}{\lambda^5 \left(e^{hc/\lambda k_B T} - 1\right)}, \quad (1)$$

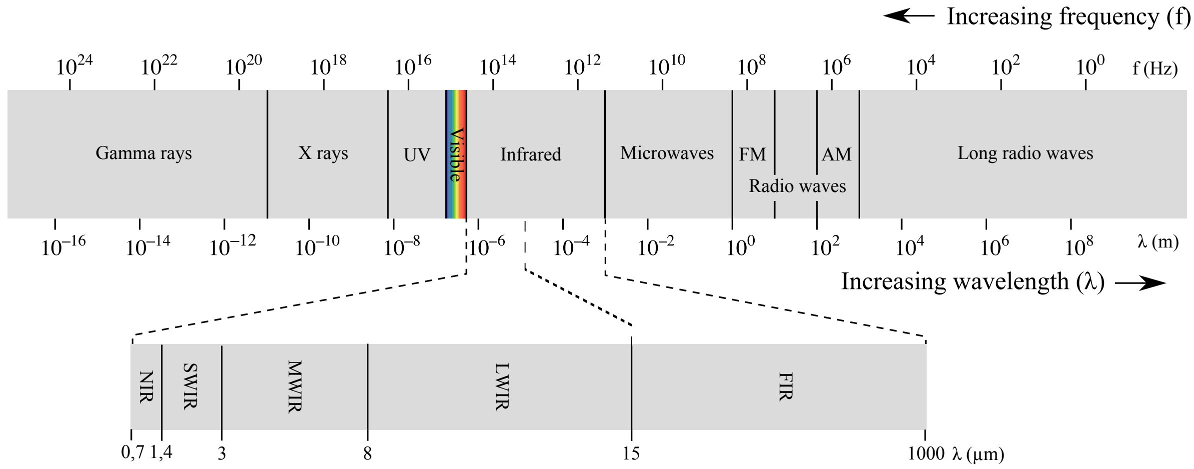

Fig. 2 The electromagnetic spectrum with sub-divided infrared spectrum.

where λ is the wavelength, h is Planck's constant ($6.626 \times 10^{-34} Js$), c the speed of light ($299,792,458 m/s$) and k_B Boltzmann's constant ($1.3806503 \times 10^{-23} J/K$).

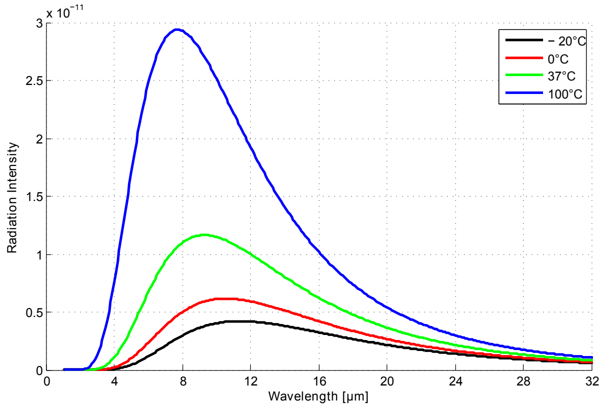

Fig. 4 Intensity of black body radiation versus wavelength at four temperatures.

As can be seen in Figure 4, the intensity peak shifts to shorter wavelengths as the temperature increases, and the intensity increases with the temperature. For extremely hot objects the radiation extends into the visible spectrum, e.g., as seen for a red-hot iron. The wavelength of the intensity peak is described by Wien's displacement law [159]:

$$\lambda_{max} = \frac{2.898 \times 10^{-3}}{T}. \quad (2)$$

Planck's wavelength distribution function, Equation 1, describes the radiation from a black body. Most materials studied in practical applications are assumed to be so called grey bodies, which have a constant scale factor of the radiation between 0 and 1. This factor is called the emissivity. For instance, polished silver has a very low emissivity (0.02) while human skin has an emissivity very close to 1 [65]. Other materials, such as gases, are selective emitters, which have specific absorption and emission bands in the thermal infrared spectrum [181]. The specific absorption and emission bands are due to the nature of the radiation, as described in the next section.

2.3 Energy States of a Molecule

The energy of a molecule can be expressed as a sum of four contributions [159]: electronic energy, due to the interactions between the molecule's electrons and nuclei; translational energy, due to the motion of the molecule's centre of mass through space; rotational energy, due to the rotation of the molecule about its centre of mass; and vibrational energy, due to the vibration of the molecule's constituent atoms:

$$E = E_{el} + E_{vib} + E_{rot} + E_{trans}. \quad (3)$$

The translational, rotational, and vibrational energies contribute to the temperature of an object.

The possible energies of a molecule are quantized, and a molecule can only exist in certain discrete energy levels. Figure 5 illustrates the relation between the electronic, vibrational, and rotational energy levels. The contribution from the translational energy is very small and is not included in this illustration.

Electromagnetic radiation can be absorbed and emitted by molecules. Incident radiation causes the molecule to rise to an excited energy state, and when it falls back to the ground state, a photon is released. Only photons with specific energies, equal to the difference between two energy levels, can be absorbed. Visible light usually causes electron transitions, with rising or falling electronic energy level. Just as for visible light, infrared light can cause transitions in the vibrational or rotational energy levels. All objects emit infrared radiation

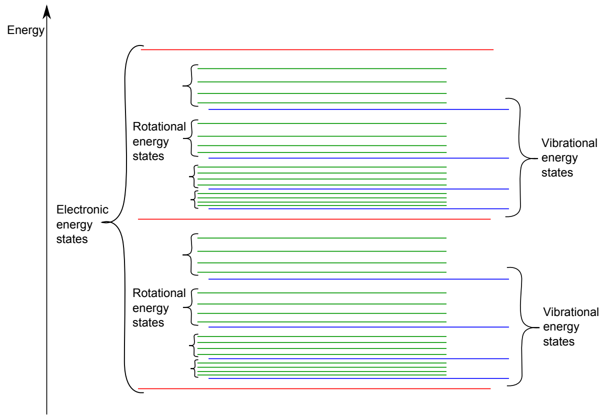

Fig. 5 Simplified illustration of the electronic, vibrational, and rotational energy states. Each line illustrates a discrete energy level that the molecule can exist in.

corresponding to their temperature. If more radiation is absorbed than emitted, the temperature of the molecule will rise until equilibrium is re-established. Likewise, the temperature will fall if more radiation is emitted than absorbed, until equilibrium is re-established.

3 Thermal Cameras

Although infrared light was discovered by William Herschel around 1800, the first infrared scanning devices and imaging instruments were not build before the late 1940s and 1950s [90]. They were built for the American military for the purpose of night vision. The first commercial products were produced in 1983 and opened up a large area of new applications.

The measurement instruments available today can be divided into three types: point sensors, line scanners, and cameras.

3.1 Camera Types

Infrared cameras can be made either as scanning devices, capturing only one point or one row of an image at a time, or using a staring array, as a two-dimensional infrared focal plane array (IRFPA) where all image elements are captured at the same time with each detector element in the array. Today IRFPA is the clearly dominant technology, as it has no moving parts, is faster, and has better spatial resolution than scanning devices [90]. Only this technology is described in the following.

The detectors used in thermal cameras are generally of two types: photon detectors or thermal detectors. Photon detectors convert the absorbed electromagnetic radiation directly into a change of the electronic energy distribution in a semiconductor by the change of the free charge carrier concentration. Thermal detectors convert the absorbed electromagnetic radiation into thermal energy causing a rise in the detector temperature. Then the electrical output of the thermal sensor is produced by a corresponding change in some physical property of material, e.g., the temperature-dependent electrical resistance in a bolometer [181].

The photon detector typically works in the MWIR band where the thermal contrast is high, making it very sensitive to small differences in the scene temperature. Also with the current technology the photon detector allows for a higher frame rate than thermal detectors. The main drawback of this type of detector is its need for cooling. The photon detector needs to be cooled to a temperature below 77 K in order to reduce thermal noise. This cooling used to be done with liquid nitrogen, but now is often implemented with a cryocooler. There is a need for service and replacement for the cryocooler due to its moving parts and helium gas seals. The overall price for a photon detector system is therefore higher than a thermal detector system, both its initial costs and its maintenance.

A thermal detector measures radiation in the LWIR band and can use different detector types, which will be described in the next section.

3.1.1 Thermal Detector Types

Uncooled thermal detectors have been developed mainly with two different types of detectors: ferroelectric detectors and microbolometers. Ferroelectric detectors take advantages of the ferroelectric phase transition in certain dielectric materials. At and near this phase transition, small fluctuations in temperature cause large changes in electrical polarization [49]. Barium Strontium Titanate (BST) is normally used as the detector material in the ferroelectric detectors.

A microbolometer is a specific type of resistor. The materials most often used in microbolometers are Vanadium Oxide (VOx) and Amorphous silicon (a-Si). The infrared radiation changes the electrical resistance of the material, which can be converted to electrical signals and processed into an image.

Today it is clear that microbolometers have more advantages over the ferroelectric sensors and the VOx technology has gained the largest market share. First of all, microbolometers have a higher sensitivity. The noise equivalent temperature difference (NETD), specifying the minimum detectable temperature difference, is 0.039 K for VOx compared to 0.1 K for BST detectors [49]. Microbolometers also have a smaller pixel size on the detector, allowing a higher spatial resolution. Furthermore, BST detectors suffer from a halo effect, which can often be seen as a dark ring around a bright object, falsely indicating a lower temperature [49]. An example of the halo effect is shown in Figure 6.

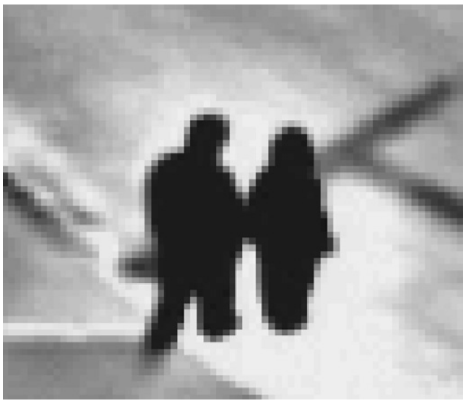

Fig. 6 Thermal image showing bright halo around a dark person [38].

3.2 The Lens

Since glass has a very low transmittance percentage for thermal radiation, a different material must be used for the lenses. Germanium is used most often. This is a grey-white metalloid material which is nearly transparent to infrared light and reflective to visible light. Germanium has a relatively high price, making the size of the lens important.

The f-number of an optical system is the ratio of the lens's focal length to the diameter of the entrance pupil. This indicates that a higher f-number reduces the price of the lens, but at the same time, when the diameter of the lens is reduced, a smaller amount of radiation reaches the detector. In order to maintain an acceptable sensitivity, uncooled cameras must have a low f-number. For cooled cameras, a higher f-number can be accepted, because the exposure time can be increased in order to keep the same radiation throughput. These properties of the lens cause the price for uncooled cameras to increase significantly with the focal length, while the price for cooled cameras only increases slightly with the focal length. For very large focal lengths, cooled cameras will become cheaper than uncooled cameras [48].

3.3 Camera Output

Modern thermal cameras appear just like visual video cameras in terms of shape and size. Figure 7 shows an example of a thermal network camera.

Fig. 7 Example of an uncooled thermal camera, AXIS Q1921.

The data transmission typically takes place via USB, Ethernet, FireWire, or RS-232. The images are represented as greyscale images with a depth from 8 to 16 bit per pixel. They are, however, often visualised in pseudo colours for better visibility for humans. Images can be compressed with standard JPEG and video can be compressed with H264 or MPEG [8]. Analogue devices use the NTSC or PAL standards [51]. Some handheld cameras are battery-driven, while most of the larger cameras need an external power supply or Power over Ethernet.

The thermal sensitivity is down to 40 mK for uncooled cameras and 20 mK for cooled devices. The spatial resolution of commercial products varies from 160 $\times$ 120 pixels to 1280 $\times$ 1024 pixels, and the field of view varies from 1° to 58° [73, 52, 7, 50].

4 Application Areas

The ability to 'see' the temperature in a scene can be a great advantage in many applications. The temperature can be important to detect specific objects, or it can provide information about, e.g., type, health, or material of the object. This section will survey the applications of thermal imaging systems with three different categories of subjects: animals and agriculture, inanimate objects, and humans.

4.1 Animals and Agriculture

4.1.1 Animals

Warm-blooded animals, such as humans, try to maintain a constant body temperature, while cold-blooded animals adapt their temperature to their surroundings. This property of warm-blooded animals makes them stand out from their surroundings in thermal images.

Warm-blooded animals can warm their body by converting food to energy. To cool down, they can sweat or pant to lose heat by water evaporation. The radiation of heat from animals depends on their insulation, such as hair, fur, or feathers, for example. The temperature distribution over the body surface can be uneven, depending on blood-circulation and respiration. In the studies of wild animals thermal imaging can be useful for diagnosis of diseases and thermoregulation, control of reproductive processes, analysis of behaviour, as well as detection and estimation of population size [31].

Diseases will often affect the general body temperature, while injuries will be visible at specific spots, e.g., caused by inflammations. Thermal imaging has thereby been proven to work as a diagnosis tool for some diseases of animals. In [71] it was observed that the temperature in the gluteal region of dairy cattle increases when the animal becomes ill and this could be detected in thermal images prior to clinical detection of the disease. If the observed animals are wild, the method of examining for a disease should be without contact with the animals. In [5] thermal cameras are used for detecting sarcoptic mange in Spanish ibex. Although conventional binoculars have higher sensitivity over a greater distance, thermal cameras can give indication of the prevalence of the disease in a herd. Thermal imaging could also be used to detect diseases among other wild animals, in [40] it is found that rabies can be detected in raccoons by observing the temperature of the nose.

The stress level of animals before slaughtering is important to the meat quality. The stress level is correlated with the blood and body temperature of the animal. It is therefore important to monitor and react to a rising temperature, e.g., during transport. The work of [185] measures the temperature of pigs' ears and finds that it is positively correlated with the concentration of cortisol and the activity of creatine kinase.

Thermal imaging can be beneficial when diagnosing lameness in horses. [194] suggests using thermal imaging for detecting inflammations and other irregularities, especially in the legs and hoofs of horses. Figure 8 shows an example of inflammation in the leg.

Analysis of the thermodynamic characteristics in ectotherm animals, such as frogs, has been carried out in [39]. They measure the temperature of different body parts of frogs during heating from $8°C$ (artificial hibernation) to $23°C$ (artificial arousal). In such experiments it is a great advantage that the measurements are taken without harming or touching the animal.

Large animals can pose a risk for traffic if they run onto the road. They can often be hard to spot with the eye, specially in the dark or haze, also if they are camouflaged beside the road. Deer are some of the animals that can be a threat to safety on the roads. In [201], they propose a system for detecting and tracking deer from a vehicle, in order to avoid collisions. Some car brands have implemented thermal cameras and screens in their cars for manual detection of unexpected hot objects [47].

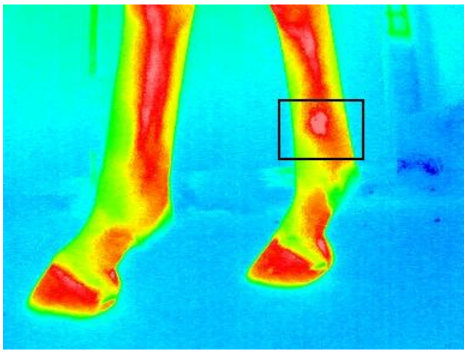

Fig. 8 The thermal image reveals inflammation in the leg of a horse. The inflamed area is marked with a black box.

Wild animals have a high risk of being injured or killed during farming routines with modern high-efficiency farming equipment. Therefore [172] proposes automatic analysis of thermal images for detection of animals hidden in the vegetation. They use a pre-processing step by filtering the image with the Laplacian of Gaussian, before using adaptive thresholding for detecting the animal.

4.1.2 Agriculture and Food

Thermal imaging systems have various applications in the agriculture and food industry. They are suitable in the food industry due to their portability, realtime imaging, and non-invasive and non-contact temperature measurement capability [59]. In food quality measurement, it is important to use a non-destructive method to avoid waste.

The two papers [179] and [59] review the use of thermal imaging in the agriculture and food industry, including both passive thermography (measuring the temperature of the scene) and active thermography (adding thermal energy to an object, and then measuring the temperature). Passive thermography is mostly used for temperature control in food manufacturing and for monitoring heat processes. Active thermography of food objects can give information about the quality, such as damage and bruises in fruits and vegetables. Bruises can be detected using active thermal imaging, due to the different thermodynamic properties in sound and bruised tissue. Thermal imaging has been applied in [27] to detect fungal infections in stored wheat. It could discriminate between healthy and infected wheat, but not between different fungal species. In [93], they classify healthy and fungal infected pistachio kernels.

4.2 Inanimate Objects

Inanimate objects do not maintain a constant temperature. Their temperature depends on both the surrounding temperature, and the amount of added energy that generates heat. Thermal images of inanimate objects depict the surface temperature of the scene. But even in a scene in equilibrium, differences in the image can be observed due to different emissivities of the observed surfaces. Thus thermal imaging can be used for analysing both temperature and material.

4.2.1 Building Inspection

Thermal cameras have been used for years for inspecting heat loss from buildings, and special hand-held imaging devices have been developed with this application in mind. Figure 9 shows an example of a thermal image of a building.

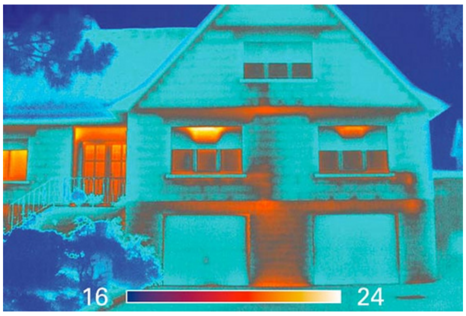

Fig. 9 Thermal image of a building, showing a higher amount of heat loss around windows and doors [149].

Normally the inspection of buildings requires manual operation of the camera and interpretation of the images to detect heat loss, e.g., as described in [3]. More automatic methods are also being investigated. In [119], an Unmanned Aerial Vehicle (UAV) is used for inspection of buildings, and the system automatically detects the heat loss from windows. Another system has been proposed, which automatically maps the images to a 3D model, eliminates windows and doors, and detects regions with high heat loss on the facade [69, 77, 162]. A thermal system has also been proposed for detecting roof leakage [4].

Besides the detection of heat loss, thermal imaging has also been used to detect other problems behind the surface: [113] proves that thermal imaging can be used to detect debonded ceramic tiles on a building finish. Termites can also be found by inspection with a thermal camera, as they produce unusual heat behind the surface in buildings [79].

For some ancient buildings, it is of interest to monitor the wall's hidden structure, the surface status, and moisture content, which can be done with a thermal camera [60]. The documentation of a building's status can also be done by combining visual and thermal images [106].

Another interesting application related to buildings is the one presented in the book *Mobile Robot Navigation with Intelligent Infrared Image* [44]. They present an outdoor robot system equipped with a thermal camera and an ultrasound sensor. In order to move around safely, the robot should be able to classify typical outdoor objects, such as trees, poles, fences, and walls, and make decisions about how to go around them. The classification of these non heat-generating objects is based on their physical properties, such as emissivity, that influence their thermal profile.

4.2.2 Gas Detection

Gasses are selective emitters, which have specific absorption and emission bands in the infrared spectrum, depending on their molecular composition. By using instruments able to measure selectable narrow infrared bands, it is possible to measure the radiation in the absorption band of a specific gas. As the radiation is absorbed by the gas, the observed area would appear as a cool cloud (usually dark) if the gas is present.

Using optical bandpass filters is applied for measuring carbon monoxide in [123]. Using a thermal spectrometer, a number of bands can be measured concurrently to analyse the gas content in the scene. In [134], they use 12 spectral bands distributed from 8.13μm to 11.56μm to detect an anomalous gas and track it in the image to locate the source of the gas leak. [107] tests a method for detecting gas leakage in landfills based on the temperature measurements of a thermal camera (8–13 μm). They conclude that it is possible, but depends on the weather conditions and climate. [157] detects gas leaks of ammonia, ethylene, and methane by measuring the spectral region 7–13 μm. Volcanic ash particles can also be detected by measuring five spectral bands between 7–14 μm [147].

4.2.3 Industrial Applications

In most electrical systems, a stable temperature over time is important in order to avoid system break-downs. Sudden hot spots can indicate faulty areas and connections, e.g., in electric circuits and heating systems.

It would obviously be of great value if devices that are starting to over-heat could be detected before they break down. One of the reasons for using thermal imaging for temperature measurement is that it is not in contact with the target. Thermal imaging can be applied as a diagnosis tool for electrical joints in power transmission systems [154], and for automatic detection of the thermal conditions of other electrical installations [78]. It can also be used to evaluate specific properties in different materials. In [125], the erosion resistance of silicon rubber composites is evaluated using a thermal camera. In metal sheet stamping processes, the mechanical energy is converted into thermal energy. An unexpected thermal distribution can be an indication of malfunctions in the object. Therefore [130] proposes a system that compares the thermal images to a simulated thermal pattern in order to find a diagnosis for the object. For more complicated objects, a 3D model is generated. [70] uses thermal imaging for measuring the molten steel level in continuous casting tundish.

For race cars, tire management is extremely important, and one of the main parameters of a tire is its temperature. [35] proposes the use of a thermal camera for dynamic analysis of the temperature of the tires during a race.

4.2.4 Fire Detection and Military

Automatic systems for detecting objects or situations that could pose a risk can be of great value in many applications. A fire detection system can be used for mobile robots. [72] proposes a system using a pan-tilt camera that can operate in two modes, either narrow field of view or wide field of view using a conic mirror. Fires are detected as hot spots, and the location is detected in order to move the robot to the source of fire. [6] proposes a hybrid system for forest fire detection composed of both thermal and visual cameras, and meteorological and geographical information, while [140] proposes a handheld thermal imaging system for airborne fire analysis.

[148] presents a gunfire detection and localisation system for military applications. Gunfire is detected in mid-wave infrared images and validated by acoustic events. The detected gunfire is mapped to a real-world location. [161] proposes using thermal imaging for mine detection. Depending on circumstances such as the ambient air temperature and soil moisture, mines can be detected using the assumption that the soil directly above the mine heats or cools at a slightly different rate than the surrounding soil. [186] uses the same idea in their system. They spray cold water over the surrounding soil, and capture the temperature distribution of the cooling soil with a thermal camera. [91] presents the idea of using thermal imaging for detecting snipers. The muzzle flash, the bullet in flight, and the sniper body can be detected.

4.3 Humans

In computer vision research, humans are often the subjects observed. Its application areas are very wide, from surveillance through entertainment to medical diagnostics. While the previously mentioned application areas often use simple image processing algorithms, such as thresholding, or even manual inspection of the images, for human systems there has been more emphasis on robust systems with automatic detection and tracking algorithms. Therefore, this part will also contain information about the specific methods.

Just as described for warm-blooded animals, humans try to maintain a constant body temperature, independent of the temperature of the surroundings. This implies that, when capturing a thermal image, the persons stand out from the background in most environments. Taking advantage of that feature could improve the detection step in many vision systems. If a person is observed from a close distance, information can be extracted about the skin temperature distribution. That can be useful for, e.g., face recognition or medical investigations.

4.3.1 Detection and Tracking of Humans

Detection of humans is the first step in many surveillance applications. General purpose systems should be robust and independent of the environment. The thermal cameras are here often a better choice than a normal visual camera. [203] proposes a system for human detection, based on the extraction of the head region and [37] proposes a detection system that uses background subtraction, gradient information, watershed algorithm and A* search in order to robustly extract the silhouettes. Similar approaches are presented in [36, 114], using Contour Saliency Maps and adaptive filters, while [184] presents a detection method based on the Shape Context Descriptor and Adaboost cascade classifier. A common detection problem is that the surroundings during summer are hotter than or equal to the human temperature. [82] tries to overcome this problem by using Mahalanobis distance between pixel values and edge orientation histograms. [53, 54] use automatic thresholding and a sorting and splitting of blobs in order to detect and count people in sports arenas, see Figure 10.

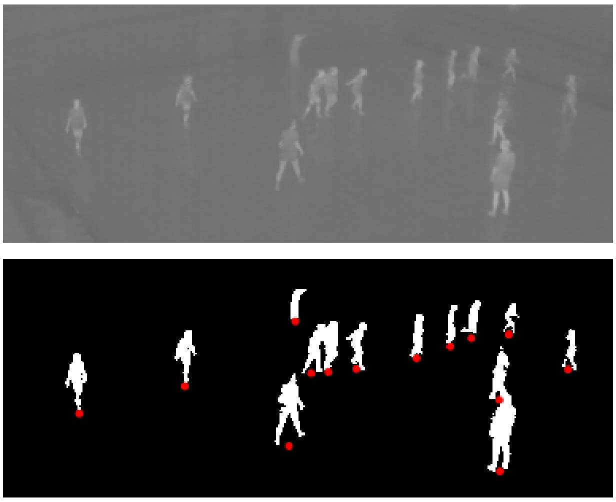

Fig. 10 Example of humans playing handball. Top image: Original thermal image. Bottom image: Binarised image with all persons marked with a red dot. [53]

Thermal cameras are very useful for the surveillance and detection of intruders, because of their ability to 'see' during the night. For trespasser detection, classification is often based on temperature and simple shape cues. Wong et al. propose two trespasser detection systems, one in which they adjust the camera to detect objects in the temperature range of humans, and then classify the objects based on the shape [191]. The other work aims to identify humans using pattern recognition to detect the human head [189]. [46] uses thresholding, and then a validation of each blob, to determine if it contains one or more persons. If it contains more than one, it will be split into two blobs. [11] proposes a real time detection and tracking system with a classification step based on a cascade of boosted classifiers.

Thermal sensors can be used in systems for the detection of fall accidents or unusual inactivity, which is an important safety tool for the independent living of especially elderly people. [164] proposes a system that uses a low resolution thermal sensor. The system gives an alarm in case of a fall detected, or in the case of inactivity over a long time period. [190] also proposes a fall detection system for private homes by analysing the shape of the detected object. In [94] a fall detection system for bathrooms are proposed, using a thermal sensor mounted above the toilet.

Analysis of more general human activity has also been performed. [63] presents a system that distinguishes between walk and run using spatio-temporal information, while [18] estimates the gait parameters by fitting a 3D kinematic model to the 2D silhouette extracted from the thermal images. In [55] different sports types are classified by the detected location of people over time. [143] proposes a system for analysing the posture of people in crowds, in order to detect people lying down. This could be useful to detect gas attacks or other threats at public places. [76] proposes a system for estimating the human body posture by finding the orientation of the upper body, and locating the major joints of the body.

Rescue robots are used during natural disasters or terrorist attacks, and are often equipped with a thermal camera in order to be able to look for victims in the dark. [118] presents a rescue robot equipped with several sensors, including thermal camera, visual camera and laser range scanner. This robot is able to detect victims in a scene and drive autonomously to the destination. [9] proposes a robot rescue system using thermal and visual camera to identify victims in a scene. For use on Unmanned Aerial Vehicles [155] proposes a human detection system that use a thermal camera to detect warm objects. The shape of the object is analysed in order to reject false detections, before the corresponding region in the colour image is processed with a cascade of boosted classifiers.

Thermal cameras are very popular in the research of pedestrian detection, due to the cameras' independence of lighting changes, which means that it will also work during the night, when most accidents between cars and pedestrians happen. One of the car-based detection systems is proposed in [21], where they present a tracking system for pedestrians. It works well with both still and moving vehicles, but some problems still remain when a pedestrian enters the scene running. [42] proposes a shape-independent pedestrian detection method. Using a thermal sensor with low spatial resolution, [116] builds a robust pedestrian detector by combining three different methods. [89] also proposes a low resolution system for pedestrian detection from vehicles. [136] proposes a pedestrian detection system, that detects people based on their temperature and dimensions and track them using a Kalman filter. In [135] they propose a detection system based on histogram of oriented phase congruency and a SVM classifier for classification of pedestrians. [16] proposes a pedestrian detection system with detection based on symmetric edges, histogram analysis and size of the object. The subsequent work [13] adds a validation step, where the detected objects are matched with a pedestrian model. [193] proposes a system that uses SVM for detection and a combination of Kalman filter prediction and mean shift for tracking.

Wide purpose pedestrian detection includes shape- and appearance-based approaches and local feature-based approaches. [33] uses a shape-based detection and an appearance-based localisation of humans. In [34] the foreground is separated from the background, after that shape cues are used to eliminate non-pedestrian objects, and appearance cues help to locate the exact position of pedestrians. A tracking algorithm is also implemented. [199] uses combinations of local features and classifiers. HOG features and Edgelets are used for detection, and Adaboost and SVM cascade are used as classifiers. [173] and [112] do also use HOG detectors and SVM classifier for pedestrian detection. [182] implements an embedded pedestrian detection system on FPGA. In [17,12] a car-based stereo-vision system has been tested, detecting warm areas and classify if they are humans, based on distance estimation, size, aspect ratio, and head shape localization. [15,128] use probabilistic template models for pedestrian classification, while [120] uses a statistical approach for head detection.

For tracking pedestrians, [138,137] use both spatial and temporal data association, the Wigner distribution, and a motion-based particle filter. [165] uses a multiple-model particle filter, and prior information about the walkways to enhance the performance. [178] does also use a particle filter, combined with two shape- and feature-based measurement models, to track humans in real time from a mobile robot. Other robot-based systems for detection and tracking are proposed in [45,25]. For the static case, when the robot is still, image differencing and thresholding are applied for human detection. When it moves, the system uses optical flow for filtering the moving foreground objects from moving scene background. [104] proposes a human tracking algorithm for mobile robots that combines a curve matching framework with Kalman filter tracking. [87, 88] propose a local feature (SURF) based method for detection of body parts and tracking of humans. The tracking part uses Kalman-based prediction of object positions to overcome the lack of colour features for distinguishing people. For scenes captured with a moving camera, the Kalman prediction is replaced by a calculation of shift vectors between frames.

4.3.2 Facial Analysis

Face detection is the first step in many applications, including face recognition, head pose analysis, or even some full person detection systems. Since the face is normally not covered by clothes, a thermal camera can capture the direct skin temperature of the face. [98] and [121] propose head detection systems based on a combination of temperature and shape.

Face recognition using thermal cameras eliminates the effects of illumination changes and eases the segmentation step, but it can also introduce some challenges due to the different heat patterns of a subject, caused by different activity levels or emotions such as anxiety. One of the very early approaches is neural networks [196]. [168,188] compare the use of thermal images in face recognition to visual images using appearance based methods. The thermal images yield better results than visual images here. However, it has not yet been tested how different activity levels of the subjects, and extreme ambient temperature, will affect the recognition rate. In [20] a thermal face recognition algorithm has been developed using the techniques of polar transformation, eigenspace projection, and classification using a multilayer perceptron. [56] tests the use of different parts of the face for facial recognition, and conclude that using the upper part of the face gives a better recognition rate than using the whole face. [22,23] propose a face recognition system using characteristic and time-invariant physiological information as features.

The recognition of common facial expressions is another task of great interest. Neural networks have also been used as an early approach here [197]. Using a sparse dataset of 120 images, showing four different expressions from one person, the system showed good results. [80] proposes a system to recognise facial expressions by analysing the geometry and local characteristics.

Also facial orientation are of interest in many vision systems. A few papers have proposed systems to estimate the head pose. [192] calculates the roll angle of frontal face images while [198] proposes a system to estimate the yaw angle of the head. [92] proposes a system for detecting the driver's posture in a car. First the face area is detected, and then the posture is classified as leftward, frontward or rightward.

Measuring the heat distribution in the face can give information about the anxiety level [141], the emotion of car drivers [95], or it can be used for automatic blush detection [66]. For such systems to work automatically, it is important that the system is able to follow the tissue of interest over time. [202] proposes such a tracking system, using a particle filter tracker. For biometric identification, [2] proposes the use of thermal 'faceprints'. These faceprints capture facial physiological features, representing the network of blood vessels under the skin[1]. [61,62] do also propose the use of thermal face images for biometric identification. They extract the superficial blood vessels from MWIR images with skeletonization. Figure 11 shows an example of thermal face and hand images. The veins are visible at the dorsum of the hand.

[1] Thermal images are also used in other biometrics such as hand veins, neck veins and arm veins [58], and palm-dorsa vein patterns [115,41,183]

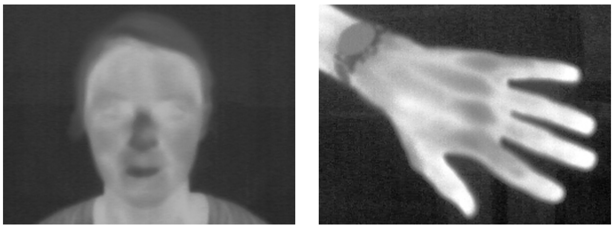

Fig. 11 Thermal images of the face or hand can be used for biometric identification.

4.3.3 Medical Analysis

Thermal imaging provides information about physiological processes through examining skin temperature distributions, which can be related to blood perfusion. In the medical area, cameras with high thermal resolution in the human temperature range are used in order to observe fine temperature differences. Thermal imaging complements the standard anatomical investigations based on X-ray and 3D scanning techniques such as CT and MR [84]. [102] and [153] review the medical applications of infrared thermography, including breast cancer detection, diabetes neuropathy, fever screening, dental diagnosis, brain imaging, etc.

Thermal imaging has been shown to reveal tumours in an early state, especially with breast cancer, as described in the survey [150]. Various other medical issues can be studied from thermal images, such as the behaviour of the ciliary muscle of the human eye [64], the pulse from the superficial temporal artery [26] or facial vasculature [57], the volumetric flow rate in superficial veins [117], or the periodic fluctuation in skin temperature [96]. Thermal imaging of the human foot has also proven to be useful in the detection of ulceration risks for diabetic patients [142].

In rehabilitation, thermal imaging can be employed to monitor and interpret communications from people with motor impairments, such as mouth opening and closing [122].

5 Image fusion

As discussed in Section 1, visual cameras and thermal cameras have both advantages and disadvantages in computer vision applications. Since the limitations of the different technologies are independent, and often do not occur simultaneously, it can be beneficial to combine these different types of images. Occlusion is a well-known problem across all modalities. Separating partly occluded persons or objects of the same temperature can be very difficult in thermal images, as they have the same pixel intensity. Including depth information or colour edges can help disambiguate in this situation.

The most common combination of cameras is thermal and visual. This is due to the low price and well-known characteristics of visual cameras and the ensuing advantages of augmenting colour with temperature.

The main challenges are how to align and fuse the different image modalities. There is not necessarily any relation between brightness level in the different spectra, thus many mutual information alignment methods are not appropriate [133]. Often, corresponding points are manually selected to calculate a planar homography, and then warp one of the images. Automatic alignment techniques that rely on the correlation between edge orientations are presented in [74, 75], and a method that calculates the homography from automatically detected keypoints is presented in [169].

The standard chessboard method for geometric calibration, correction of lens distortion, and alignment of the cameras relies on colour difference, and can not be used for thermal cameras without some changes. [30, 146] report that when heating the board with a flood lamp, the difference in emissivity of the colours will result in an intensity difference in the thermal image. However, a more crisp chessboard pattern can be obtained by constructing a chessboard of two different materials, with large difference in thermal emissivity and/or temperature [180]. This approach is also applied in [68] using a copper plate with milled checker patterns in front of a different base material, and in [195] with a metal wire in front of a plastic board. When these special chessboards are heated by a heat gun, hairdryer or similar, a clear chessboard pattern will be visible in the thermal image, due to the different emissivity of the materials. At the same time, it is also visible in the visual image, due to colour difference. Figure 12 shows thermal and RGB pictures from a calibration test. The chessboard consists of two cardboard sheets, where the white base sheet has been heated right before assembling the board.

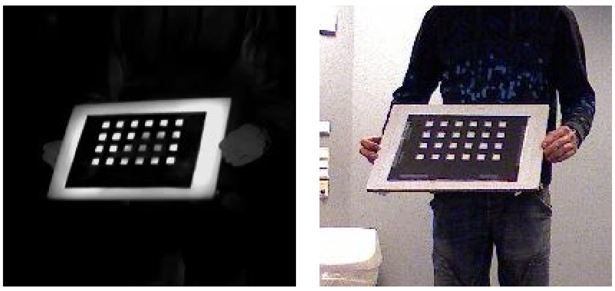

Fig. 12 Thermal and visible image of a calibration chessboard consisting of two cardboard sheets, where only the white layer has been heated before assembling.

Fusion can take place at different levels of the processing, often described as pixel level, feature level, or decision level [204]. In pixel level fusion, the images need to be spatially registered, as discussed above, so that the same pixel positions of all images correspond to the same location in the real world. The images are then combined pixel-by-pixel using a fusion algorithm. With feature level fusion, the features are found in all images individually and then fused into a joint feature set. Decision level fusion follows the individual processing until the evaluation of the observed scene is done. At the end-stage, the decisions, or classifications, are combined into one result. The choice of fusion level will depend on the application.

Methods for fusing visible and infrared videos are discussed in [152] and [163], where the two images are aligned and combined using an overlay image with the heat information. In [133] two fusion methods are compared, one named a general fusion model (pixel level) and the other method named a combination module (feature level). The combination module has the best performance tested over six sequences. [160] proposes a combination of curvelet and wavelet transforms, as well as a discrete wavelet packet transform approach for fusing visual and thermal images. In [28] a statistical approach based on expectation maximization is proposed. [103] uses an adaptive weighting method, which enhances unnatural objects in each modality before fusion. An alternative approach is to keep both colour and thermal information as separate channels in a new 'Red-Green-Blue-Thermal' video format [171].

The spatial resolution of thermal cameras is still low, and the price for the best resolution available is high. Using cheap thermal sensors with a low spatial resolution can still improve surveillance when combined with the use of a visual camera. [86] uses a thermal sensor with 16×16 pixels to give an indication of where to search in the visual image. They concentrate on calibrating the two cameras and find the correspondence between the images. By fusing the visual and thermal videos, super-resolution of the thermal images can be constructed [85]. A prototype using three cameras to combine both the visual, NIR, and LWIR bands is proposed in [175]. Sensors other than visual cameras can also be combined with thermal cameras in fusion systems. [43] fuses the data from a thermal camera and a laser scanner to obtain robust pedestrian detection for tracking. [158] fuses near-infrared sensors and low resolution far-infrared sensors in order to obtain a low-cost night vision system.

Fused image systems find application in a variety of areas, which we now summarize. In surveillance systems it is popular to use fused image modalities, due to the necessity of a robust system that can work both night and day, indoors and outdoors [101,132]. In both surveillance and night vision systems for cars, the detection of pedestrians can be improved by fusing the image modalities [177,131,108,110,111,151,156]. General purpose human detection systems are proposed in [81,36,38,174]. [109] presents a surveillance system that also estimates the attention field of the detected humans and [83] fuses the visual and thermal images for a robust foreground detection in tele-immersive spaces. [32] proposes a combined human detection and recognition system for a robot in domestic environment. Human tracking systems using fused images are proposed in [176,200,1]. [105] uses visual stereo cameras and a thermal camera, while [99,100,14] test different combinations of stereo and single cameras of both colour and thermal types.

Face detection and face recognition have been thoroughly investigated and standard methods exist using visual cameras. However, illumination changes still have a negative impact on the performance of these systems [205]. Research has been conducted on whether these problems could be overcome by extending the systems with a thermal sensor. [166] shows a significant improvement by fusing the visible and thermal images in a time-lapse experiment. Work has been done on face recognition using both pixel-level fusion [127, 97,19], feature-level fusion [167], and decision-level fusion [145,129,29]. [67] proposes fusion on both pixel- and decision-level, while [10] tests two different fusion schemes. They all report an improved performance when fusing the different image modalities.

6 Discussion

Although the price of thermal cameras is still significantly higher than the price of comparable visual cameras, the hardware cost is continuously falling and the diversity of cameras is becoming wider. Simple sensors, such as the cheap pyroelectric infrared (PIR) sensor, have for many years been applied as motion detectors for light switch control, burglar alarm, etc. Although no image can be provided by this type of sensor, it can be sufficient for detecting a moving human or large animal. Moving towards thermal cameras, infrared array sensors can read temperature values in a coarse image. These sensors make it possible to analyse the movement, e.g. direction and speed, and can be used for instance in entrance counting systems. The price for these sensors are less than 50$ for 8×8 pixel arrays with $\pm 2.5°C$ temperature accuracy [139]. The price increases with the resolution, framerate, and accuracy, through uncooled cameras to high-end, specialised cooled cameras, with specifications up to 1280×1024 pixels and 130 fps. Some cameras come with even higher framerate, or optical zoom. The price of these high-end cameras can exceed 100,000$.

As seen in this survey, the wide range of cameras opens up for a great diversity of applications of thermal cameras. Each research field has specific needs for, e.g., resolution, field of view, thermal sensitivity, price, or size of the camera. It is therefore expected that the diversity of cameras available will become even larger within the next few years, not only focusing on high-end cameras.

Thermal imaging has found use in two different types of problems: the analysis of known subjects and the detection of unknown subjects. In the first problem, both the subjects and their location in the image are known, and the properties of the subjects can be analysed. The results could be the type of material, condition, or health. The methods used here are often simply the registration of the temperature or even a manual inspection of the images. If computer vision methods are used, often they are just simple algorithms, such as thresholding and blob detection. For the second problem, either the type of objects or their location in the image are unknown. The most important step in this type of problem is normally the detection and classification of objects. The goal here is more often to design an automatic system, e.g., for the detection or tracking of specific objects. More advanced computer vision algorithms can be applied here in order to design a robust and automatic system. In applications where the subject has a different temperature than the surroundings, thermal cameras can significantly ease the detection step compared to visual cameras.

Methods for both analysis of known subjects and detection of unknown subjects are rapidly expanding due to the lower prices and greater availability of thermal cameras. In the case with known subjects, thermal cameras could be viewed as an alternative to a non-contact thermometer. In the last case, the thermal camera is seen more as an alternative to a visual camera, and therefore currently of greater interest from a computer vision point of view. However, the general trend in modern society is the implementation of automation. With this in mind, it is expected that manual and semi-automatic image analysis will gradually be replaced with automatic vision systems, as these become more robust.

The usual disadvantages of changing illumination and the need for active lighting in dark conditions are eliminated with the thermal sensor. Moreover, in the case of surveillance, the use of thermal imaging does not raise as many privacy concerns as the use of visual imaging does. However, new challenges often appear with a new type of sensor. For thermal imaging the lack of texture information can be a disadvantage in some systems, and reflections of the thermal radiation can be a problem in surfaces with high reflectance. For the thermal cameras to stand alone in surveillance purposes, reasonable priced cameras with higher resolution, effective optical zoom, or wide angle lenses are still desired. In order to overcome some of these challenges it can be advantageous to combine thermal images with other image modalities in many applications. However, there is still a lack of an easy and standardised way to calibrate thermal cameras with other sensors. This must be solved in order to make these types of systems practical. A few pre-calibrated thermal-visual camera set-ups exist today [50, 7], and it is expected to see more of these combined systems in the future.

With more and more sensors becoming available, such as 3D, near-infrared, and thermal, the usual choice of a visual camera is harder to justify. This survey has shown that thermal sensors have advantages in a diversity of applications, and the fusion of different sensors improves the results in some applications. For the future development of vision systems, a careful choice of sensor can open up both new applications as well as alternative features for improving the performance of current applications.

References

1. Airouche, M., Bentabet, L., Zelmat, M., Gao, G.: Pedestrian tracking using color, thermal and location cue measurements: a DSmT-based framework. Machine Vision and Applications **23**, 999–1010 (2012)
2. Akhloufi, M., Bendada, A.: Thermal faceprint: A new thermal face signature extraction for infrared face recognition. In: Canadian Conference on Computer and Robot Vision (2008)
3. Al-Kassir, A.R., Fernandez, J., Tinaut, F., Castro, F.: Thermographic study of energetic installations. Applied Thermal Engineering **25**(23), 183–190 (2005)
4. Angaitkar, P., Saxena, K., Gupta, N., Sinhal, A.: Enhancement of infrared image for roof leakage detection. In: International Conference on Emerging Trends in Computing, Communication and Nanotechnology (2013)
5. Arenas, A.J., Gómez, F., Salas, R., Carrasco, P., Borge, C., Maldonado, A., OBrien, D.J., Martínez-Moreno, F.: An evaluation of the application of infrared thermal imaging to the tele-diagnosis of sarcoptic mange in the spanish ibex (capra pyrenaica). Veterinary Parasitology **109**(12), 111–117 (2002)
6. Arrue, B.C., Ollero, A., Matinez de Dios, J.R.: An intelligent system for false alarm reduction in infrared forest-fire detection. IEEE Intelligent Systems and their Applications **15**(3), 64–73 (2000)

7. AXIS Communications: AXIS Network Cameras (2012). URL http://www.axis.com/products/video/camera/index.htm
8. AXIS Communications: Q1922 datasheet (2012). URL http://www.axis.com/files/datasheet/ds_q1922_q1922-e_46221_en_1207_lo.pdf
9. Aziz, M.Z., Mertsching, B.: Survivor search with autonomous UGVs using multimodal overt attention. In: IEEE International Workshop on Safety Security and Rescue Robotics (2010)
10. Bebis, G., Gyaourova, A., Singh, S., Pavlidis, I.: Face recognition by fusing thermal infrared and visible imagery. Image and Vision Computing **24**(7), 727–742 (2006)
11. Benezeth, Y., Emile, B., Laurent, H., Rosenberger, C.: A real time human detection system based on far infrared vision. In: Image and Signal Processing, *Lecture Notes in Computer Science*, vol. 5099, pp. 76–84. Springer-Verlag, Berlin (2008)
12. Bertozzi, M., Broggi, A., Caraffi, C., Rose, M.D., Felisa, M., Vezzoni, G.: Pedestrian detection by means of far-infrared stereo vision. Computer Vision and Image Understanding **106**(23), 194–204 (2007)
13. Bertozzi, M., Broggi, A., Fascioli, A., Graf, T., Meinecke, M.M.: Pedestrian detection for driver assistance using multiresolution infrared vision. IEEE Transactions on Vehicular Technology **53**(6), 1666–1678 (2004)
14. Bertozzi, M., Broggi, A., Felisa, M., Vezzoni, G., Del Rose, M.: Low-level pedestrian detection by means of visible and far infra-red tetra-vision. In: IEEE Intelligent Vehicles Symposium (2006)
15. Bertozzi, M., Broggi, A., Gomez, C.H., Fedriga, R.I., Vezzoni, G., Del Rose, M.: Pedestrian detection in far infrared images based on the use of probabilistic templates. In: IEEE Intelligent Vehicles Symposium (2007)
16. Bertozzi, M., Broggi, A., Grisleri, P., Graf, T., Meinecke, M.: Pedestrian detection in infrared images. In: IEEE Intelligent Vehicles Symposium (2003)
17. Bertozzi, M., Broggi, A., Lasagni, A., Rose, M.D.: Infrared stereo vision-based pedestrian detection. In: IEEE Intelligent Vehicles Symposium (2005)
18. Bhanu, B., Han, J.: Kinematic-based human motion analysis in infrared sequences. In: Sixth IEEE Workshop on Applications of Computer Vision (2002)
19. Bhowmik, M., De, B., Bhattacharjee, D., Basu, D., Nasipuri, M.: Multisensor fusion of visual and thermal images for human face identification using different SVM kernels. In: IEEE Long Island Systems, Applications and Technology Conference (2012)
20. Bhowmik, M.K., Bhattacharjee, D., Nasipuri, M., Basu, D.K., Kundu, M.: Classification of polar-thermal eigenfaces using multilayer perceptron for human face recognition. In: IEEE Region 10 and the Third international Conference on Industrial and Information Systems (2008)
21. Binelli, E., Broggi, A., Fascioli, A., Ghidoni, S., Grisleri, P., Graf, T., Meinecke, M.: A modular tracking system for far infrared pedestrian recognition. In: IEEE Intelligent Vehicles Symposium (2005)
22. Buddharaju, P., Pavlidis, I.T., Tsiamyrtzis, P.: Pose-invariant physiological face recognition in the thermal infrared spectrum. In: Conference on Computer Vision and Pattern Recognition Workshop (2006)
23. Buddharaju, P., Pavlidis, I.T., Tsiamyrtzis, P., Bazakos, M.: Physiology-based face recognition in the thermal infrared spectrum. IEEE Transactions on Pattern Analysis and Machine Intelligence **29**(4), 613–626 (2007)
24. Byrnes, J.: Unexploded Ordnance Detection and Mitigation. Springer-Verlag, Berlin (2009)
25. Castillo, J.C., Serrano-Cuerda, J., Fernández-Caballero, A., López, M.T.: Segmenting humans from mobile thermal infrared imagery. In: Proceedings of the 3rd International Work-Conference on The Interplay Between Natural and Artificial Computation: Part II: Bioinspired Applications in Artificial and Natural Computation. Springer-Verlag, Berlin (2009)
26. Chekmenev, S.Y., Farag, A.A., Essock, E.A.: Thermal imaging of the superficial temporal artery: An arterial pulse recovery model. In: IEEE Conference on Computer Vision and Pattern Recognition (2007)
27. Chelladurai, V., Jayas, D.S., White, N.D.G.: Thermal imaging for detecting fungal infection in stored wheat. Journal of Stored Products Research **46**(3), 174–179 (2010)
28. Chen, S., Leung, H.: An EM-CI based approach to fusion of IR and visual images. In: 12th International Conference on Information Fusion (2009)
29. Chen, X., Flynn, P.J., Bowyer, K.W.: IR and visible light face recognition. Computer Vision and Image Understanding **99**(3), 332–358 (2005)
30. Cheng, S.Y., Park, S., Trivedi, M.: Multiperspective thermal ir and video arrays for 3d body tracking and driver activity analysis. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2005)
31. Cilulko, J., Janiszewski, P., Bogdaszewski, M., Szczygielska, E.: Infrared thermal imaging in studies of wild animals. European Journal of Wildlife Research **59**(1), 17–23 (2013)
32. Correa, M., Hermosilla, G., Verschae, R., Ruiz-del Solar, J.: Human detection and identification by robots using thermal and visual information in domestic environments. Journal of Intelligent & Robotic Systems **66**, 223–243 (2012)
33. Dai, C., Zheng, Y., Li, X.: Layered representation for pedestrian detection and tracking in infrared imagery. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshop (2005)
34. Dai, C., Zheng, Y., Li, X.: Pedestrian detection and tracking in infrared imagery using shape and appearance. Computer Vision and Image Understanding **106**(2-3), 288–299 (2007)
35. Danese, G., Giachero, M., Leporati, F., Nazzicari, N., Nobis, M.: An embedded acquisition system for remote monitoring of tire status in F1 race cars through thermal images. In: 11th EUROMICRO Conference on Digital System Design Architectures, Methods and Tools (2008)
36. Davis, J.W., Keck, M.A.: A two-stage template approach to person detection in thermal imagery. In: Seventh IEEE Workshops on Application of Computer Vision (2005)
37. Davis, J.W., Sharma, V.: Robust detection of people in thermal imagery. In: Proceedings of the 17th International Conference on Pattern Recognition (2004)
38. Davis, J.W., Sharma, V.: Background-subtraction using contour-based fusion of thermal and visible imagery. Computer Vision and Image Understanding **106**(23), 162–182 (2007)
39. Dikic, D., Kolaric, D., Lisicic, D., Benkovic, V., Horvat-Knezevic, A., Tadic, Z., Skolnik-Gadanac, K., Orsolic, N.: Use of thermography in studies of thermodynamics in frogs exposed to different ambiental temperatures. In: ELMAR (2011)

40. Dunbar, M.R., MacCarthy, K.A.: Use of infrared thermography to detect signs of rabies infection in raccoons (procyon lotor). Journal of Zoo and Wildlife Medicine **37**(4), 518–523 (2006)
41. Fan, K.C., Lin, C.L.: The use of thermal images of palmdorsa vein-patterns for biometric verification. In: 17th International Conference on Pattern Recognition (2004)
42. Fang, Y., Yamada, K., Ninomiya, Y., Horn, B.K.P., Masaki, I.: A shape-independent method for pedestrian detection with far-infrared images. IEEE Transactions on Vehicular Technology **53**(6), 1679–1697 (2004)
43. Fardi, B., Schuenert, U., Wanielik, G.: Shape and motion-based pedestrian detection in infrared images: A multi sensor approach. In: IEEE Intelligent Vehicles Symposium (2005)
44. Fehlman, W.L., Hinders, M.K.: Mobile Robot Navigation with Intelligent Infrared Image. Springer-Verlag, Berlin (2010)
45. Fernández-Caballero, A., Castillo, J.C., Martínez-Cantos, J., Martínez-Tomás, R.: Optical flow or image subtraction in human detection from infrared camera on mobile robot. Robotics and Autonomous Systems **58**(12), 1273–1281 (2010)
46. Fernández-Caballero, A., Castillo, J.C., Serrano-Cuerda, J., Maldonado-Bascón, S.: Real-time human segmentation in infrared videos. Expert Systems with Applications **38**(3), 2577 – 2584 (2011)
47. FLIR: BMW incorporates thermal imaging cameras in its cars. Application story (2011). FLIR Commercial Vision Systems B.V.
48. FLIR: Cooled versus uncooled cameras for long range surveillance. Tehnical note (2011). FLIR Commercial Vision Systems B.V.
49. FLIR: Uncooled detectors for thermal imaging cameras. Tehnical note (2011). FLIR Commercial Vision Systems B.V.
50. FLIR Systems Inc.: FLIR product overview (2012). URL http://www.flir.com/cs/emea/en/view/?id=42100
51. FLIR Systems Inc.: FLIR SR-series (2012). URL http://www.flir.com/cs/emea/en/view/?id=41864
52. Fluke Corporation: Infrared cameras and thermal cameras by fluke (2012). URL http://www.fluke.com/Fluke/usen/products/category .htm?category=THG-BST&parent=THG
53. Gade, R., Jørgensen, A., Moeslund, T.B.: Occupancy analysis of sports arenas using thermal imaging. In: Proceedings of the International Conference on Computer Vision and Applications (2012)
54. Gade, R., Jørgensen, A., Moeslund, T.B.: Long-term occupancy analysis using graph-based optimisation in thermal imagery. In: IEEE Conference on Computer Vision and Pattern Recognition (2013)
55. Gade, R., Moeslund, T.B.: Sports type classification using signature heatmaps. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops (2013)
56. Gault, T., Mostafa, E., Farag, A., Farag, A.: Less is more: Cropping to improve facial recognition with thermal images. In: International Conference on Multimedia Technology (2011)
57. Gault, T.R., Farag, A.A.: A fully automatic method to extract the heart rate from thermal video. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops (2013)
58. Gnee, N.S.: A study of hand vein, neck vein and arm vein extraction for authentication. In: 7th International Conference on Information, Communications and Signal Processing (2009)
59. Gowen, A.A., Tiwari, B.K., Cullen, P.J., McDonnell, K., O'Donnell, C.P.: Applications of thermal imaging in food quality and safety assessment. Trends in Food Science and Technology **21**(4), 190–200 (2010)
60. Grinzato, E., Bison, P., Marinetti, S.: Monitoring of ancient buildings by the thermal method. Journal of Cultural Heritage **3**(1), 21–29 (2002)
61. Guzman, A., Goryawala, M., Adjouadi, M.: Generating thermal facial signatures using thermal infrared images. In: IEEE International Conference on Emerging Signal Processing Applications (2012)
62. Guzman, A.M., Goryawala, M., Wang, J., Barreto, A., Andrian, J., Rishe, N., Adjouadi, M.: Thermal imaging as a biometrics approach to facial signature authentication. IEEE Journal of Biomedical and Health Informatics **17**(1), 214–222 (2013)
63. Han, J., Bhanu, B.: Human activity recognition in thermal infrared imagery. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2005)
64. Harangi, B., Csordás, T., Hajdu, A.: Detecting the excessive activation of the ciliaris muscle on thermal images. In: IEEE 9th International Symposium on Applied Machine Intelligence and Informatics (2011)
65. Hardy, J.D.: The radiation of heat from the human body. III. the human skin as a black-body radiator. In: The Journal of Clinical Investigations, vol. 13(4), pp. 615–620. American Society for Clinical Investigation (1934)
66. Harmer, K., Yue, S., Guo, K., Adams, K., Hunter, A.: Automatic blush detection in "concealed information" test using visual stimuli. In: International Conference of Soft Computing and Pattern Recognition (2010)
67. Heo, J., Kong, S.G., Abidi, B.R., Abidi, M.A.: Fusion of visual and thermal signatures with eyeglass removal for robust face recognition. In: Conference on Computer Vision and Pattern Recognition Workshops (2004)
68. Hilsenstein, V.: Surface reconstruction of water waves using thermographic stereo imaging. In: Proceedings of Image and Vision Computing New Zealand (2005)
69. Hoegner, L., Stilla, U.: Thermal leakage detection on building facades using infrared textures generated by mobile mapping. In: Joint Urban Remote Sensing Event (2009)
70. Hu, Z., Xie, Z., Ci, Y., Wei, W.: Molten steel level measuring method by thermal image analysis in tundish. In: Recent Advances in Computer Science and Information Engineering, *Lecture Notes in Electrical Engineering*, vol. 129, pp. 361–367. Springer Berlin Heidelberg (2012)
71. Hurnik, J.F., Boer, S.D., Webster, A.B.: Detection of health disorders in dairy cattle utilizing a thermal infrared scanning technique. Canadian Journal of Animal Science **64**(4), 1071–1073 (1984)
72. Hwang, J.H., Jun, S., Kim, S.H., Cha, D., Jeon, K., Lee, J.: Novel fire detection device for robotic fire fighting. In: International Conference on Control Automation and Systems (2010)
73. Infrared Integrated Systems Ltd: Thermal imaging cameras by Irisys (2012). URL http://www.irisys.co.uk/thermal-imaging/
74. Irani, M., Anandan, P.: Robust multi-sensor image alignment. In: Sixth International Conference on Computer Vision (1998)
75. Istenic, R., Heric, D., Ribaric, S., Zazula, D.: Thermal and visual image registration in hough parameter space. In: 14th International Workshop on Systems, Signals

and Image Processing and 6th EURASIP Conference focused on Speech and Image Processing, Multimedia Communications and Services (2007)
76. Iwasawa, S., Ebihara, K., Ohya, J., Morishima, S.: Real-time estimation of human body posture from monocular thermal images. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (1997)
77. Iwaszczuk, D., Hoegner, L., Stilla, U.: Matching of 3D building models with IR images for texture extraction. In: Joint Urban Remote Sensing Event (2011)
78. Jadin, M.S., Ghazali, K.H., Taib, S.: Thermal condition monitoring of electrical installations based on infrared image analysis. In: Saudi International Electronics, Communications and Photonics Conference (2013)
79. James, K., Rice, D.: Finding termites with thermal imaging. In: InfraMation (2002)
80. Jiang, G., Kang, L.: Character analysis of facial expression thermal image. In: IEEE/ICME International Conference on Complex Medical Engineering (2007)
81. Jiang, L., Tian, F., Shen, L.E., Wu, S., Yao, S., Lu, Z., Xu, L.: Perceptual-based fusion of IR and visual images for human detection. In: International Symposium on Intelligent Multimedia, Video and Speech Processing (2004)
82. Jo, A., Jang, G.J., Seo, Y., Park, J.S.: Performance improvement of human detection using thermal imaging cameras based on mahalanobis distance and edge orientation histogram. In: Information Technology Convergence, *Lecture Notes in Electrical Engineering*, vol. 253, pp. 817–825 (2013)
83. Johnson, M.J., Bajcsy, P.: Integration of thermal and visible imagery for robust foreground detection in tele-immersive spaces. In: 11th International Conference on Information Fusion (2008)
84. Jones, B.F., Plassmann, P.: Digital infrared thermal imaging of human skin. IEEE Engineering in Medicine and Biology Magazine **21**(6), 41–48 (2002)
85. Jones, G., Harding, C., Leung, V.: Fusion of data from visual and low-resolution thermal cameras for surveillance. IEE Seminar Digests (10062), 17–17 (2003)
86. Jones, G.D., Hodgetts, M.A., Allsop, R.E., Sumpter, N., Vicencio-Silva, M.A.: A novel approach for surveillance using visual and thermal images. In: A DERA/IEE Workshop on Intelligent Sensor Processing, pp. 9/1–9/19 (2001)
87. Jüngling, K., Arens, M.: Feature based person detection beyond the visible spectrum. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2009)
88. Jüngling, K., Arens, M.: Local feature based person detection and tracking beyond the visible spectrum. In: Machine Vision Beyond Visible Spectrum, *Augmented Vision and Reality*, vol. 1, pp. 3–32. Springer-Verlag, Berlin (2011)
89. Kallhammer, J.E., Eriksson, D., Granlund, G., Felsberg, M., Moe, A., Johansson, B., Wiklund, J., Forssen, P.E.: Near zone pedestrian detection using a low-resolution FIR sensor. In: IEEE Intelligent Vehicles Symposium (2007)
90. Kaplan, H.: Practical Applications of Infrared Thermal Sensing and Imaging Equipment, third edn. SPIE Press (2007)
91. Kastek, M., Dulski, R., Trzaskawka, P., Sosnowski, T., Madura, H.: Concept of infrared sensor module for sniper detection system. In: 35th International Conference on Infrared Millimeter and Terahertz Waves (2010)
92. Kato, T., Fujii, T., Tanimoto, M.: Detection of driver's posture in the car by using far infrared camera. In: IEEE Intelligent Vehicles Symposium (2004)
93. Kheiralipour, K., Ahmadi, H., Rajabipour, A., Rafiee, S., Javan-Nikkhah, M., Jayas, D.: Development of a new threshold based classification model for analyzing thermal imaging data to detect fungal infection of pistachio kernel. Agricultural Research **2**(2), 127–131 (2013)
94. Kido, S., Miyasaka, T., Tanaka, T., Shimizu, T., Saga, T.: Fall detection in toilet rooms using thermal imaging sensors. In: IEEE/SICE International Symposium on System Integration (2009)
95. Kolli, A., Fasih, A., Al Machot, F., Kyamakya, K.: Non-intrusive car driver's emotion recognition using thermal camera. In: Joint 3rd Int'l Workshop on Nonlinear Dynamics and Synchronization and 16th Int'l Symposium on Theoretical Electrical Engineering (2011)
96. Kondo, K., Kakuta, N., Chinzei, T., Nasu, Y., Suzuki, T., Saito, T., Wagatsuma, A., Ishigaki, H., Mabuchi, K.: Thermal rhythmography—Topograms of the spectral analysis of fluctuations in skin temperature. In: 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2001)
97. Kong, S., Heo, J., Boughorbel, F., Zheng, Y., Abidi, B., Koschan, A., Yi, M., Abidi, M.: Multiscale fusion of visible and thermal IR images for illumination-invariant face recognition. International Journal of Computer Vision **71**, 215–233 (2007)
98. Krotosky, S., Cheng, S., Trivedi, M.: Face detection and head tracking using stereo and thermal infrared cameras for "smart" airbags: A comparative analysis. In: The 7th International IEEE Conference on Intelligent Transportation Systems (2004)
99. Krotosky, S.J., Trivedi, M.M.: On color-, infrared-, and multimodal-stereo approaches to pedestrian detection. IEEE Transactions on Intelligent Transportation Systems **8**(4), 619–629 (2007)
100. Krotosky, S.J., Trivedi, M.M.: Person surveillance using visual and infrared imagery. IEEE Transactions on Circuits and Systems for Video Technology **18**(8), 1096–1105 (2008)
101. Kumar, P., Mittal, A., Kumar, P.: Fusion of thermal infrared and visible spectrum video for robust surveillance. In: Computer Vision, Graphics and Image Processing, *Lecture Notes in Computer Science*, vol. 4338, pp. 528–539. Springer-Verlag, Berlin (2006)
102. Lahiri, B., Bagavathiappan, S., Jayakumar, T., Philip, J.: Medical applications of infrared thermography: A review. Infrared Physics & Technology **55**(4), 221–235 (2012)
103. Lallier, E., Farooq, M.: A real time pixel-level based image fusion via adaptive weight averaging. In: Third International Conference on Information Fusion (2000)
104. Lee, S., Shah, G., Bhattacharya, A., Motai, Y.: Human tracking with an infrared camera using a curve matching framework. EURASIP Journal on Advances in Signal Processing **2012**, 1–15 (2012)
105. Lee, S.K., McHenry, K., Kooper, R., Bajcsy, P.: Characterizing human subjects in real-time and three-dimensional spaces by integrating thermal-infrared and visible spectrum cameras. In: IEEE International Conference on Multimedia and Expo (2009)
106. Lerma, J.L., Mileto, C., Vegas, F., Cabrelles, M.: Visible and thermal IR documentation of a masonry brickwork building. In: CIPA XXI International Symposium, vol. XXXVI-5/C53, pp. 456–459. International Archives of

the Photogrammetry, Remote Sensing and Spatial Information Sciences (2007)
107. Lewis, A.W., Yuen, S.T.S., Smith, A.J.R.: Detection of gas leakage from landfills using infrared thermography—Applicability and limitations. Waste Management and Research **21**(5), 436–447 (2003)
108. Leykin, A., Hammoud, R.: Robust multi-pedestrian tracking in thermal-visible surveillance videos. In: Conference on Computer Vision and Pattern Recognition Workshops (2006)
109. Leykin, A., Hammoud, R.: Real-time estimation of human attention field in LWIR and color surveillance videos. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2008)
110. Leykin, A., Hammoud, R.: Pedestrian tracking by fusion of thermal-visible surveillance videos. Machine Vision and Applications **21**, 587–595 (2010)
111. Leykin, A., Ran, Y., Hammoud, R.: Thermal-visible video fusion for moving target tracking and pedestrian classification. In: IEEE Conference on Computer Vision and Pattern Recognition (2007)
112. Li, W., Zheng, D., Zhao, T., Yang, M.: An effective approach to pedestrian detection in thermal imagery. In: Eighth International Conference on Natural Computation (2012)
113. Li, Z., Yao, W., Lee, S., Lee, C., Yang, Z.: Application of infrared thermography technique in building finish evaluation. Journal of Nondestructive Evaluation **19**, 11–19 (2000)
114. Li, Z., Zhang, J., Wu, Q., Geers, G.: Feature enhancement using gradient salience on thermal image. In: International Conference on Digital Image Computing: Techniques and Applications (2010)
115. Lin, C.L., Fan, K.C.: Biometric verification using thermal images of palm-dorsa vein patterns. IEEE Transactions on Circuits and Systems for Video Technology **14**(2), 199–213 (2004)
116. Mahlisch, M., Oberlander, M., Lohlein, O., Gavrila, D., Ritter, W.: A multiple detector approach to low-resolution FIR pedestrian recognition. In: IEEE Intelligent Vehicles Symposium (2005)
117. Mahmoud, A., EL-Barkouky, A., Farag, H., Graham, J., Farag, A.: A non-invasive method for measuring blood flow rate in superficial veins from a single thermal image. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops (2013)
118. Mano, H., Kon, K., Sato, N., Ito, M., Mizumoto, H., Goto, K., Chatterjee, R., Matsuno, F.: Treaded control system for rescue robots in indoor environment. In: IEEE International Conference on Robotics and Biomimetics (2009)
119. Martinez-De Dios, J.R., Ollero, A.: Automatic detection of windows thermal heat losses in buildings using UAVs. In: World Automation Congress (2006)
120. Meis, U., Oberlander, M., Ritter, W.: Reinforcing the reliability of pedestrian detection in far-infrared sensing. In: IEEE Intelligent Vehicles Symposium (2004)
121. Mekyska, J., Espinosa-Duro and, V., Faundez-Zanuy, M.: Face segmentation: A comparison between visible and thermal images. In: IEEE International Carnahan Conference on Security Technology (2010)
122. Memarian, N., Chau, T., Venetsanopoulos, A.N.: Application of infrared thermal imaging in rehabilitation engineering: Preliminary results. In: IEEE Toronto International Conference Science and Technology for Humanity (2009)
123. Meneses, J., Briz, S., de Castro, A.J., Melendez, J., Lopez, F.: A new method for imaging of carbon monoxide in combustion environments. Review of Scientific Instruments **68**(6), 2568–2573 (1997)
124. MESA Imaging AG: MESA Imaging SwissRanger (2012). URL http://www.mesa-imaging.ch/index.php
125. Meyer, L.H., Jayaram, S.H., Cherney, E.A.: A novel technique to evaluate the erosion resistance of silicone rubber composites for high voltage outdoor insulation using infrared laser erosion. IEEE Transactions on Dielectrics and Electrical Insulation **12**(6), 1201–1208 (2005)
126. Microsoft: Kinect (2012). URL http://www.xbox.com/en-US/KINECT
127. Moon, S., Kong, S.G., Yoo, J.H., Chung, K.: Face recognition with multiscale data fusion of visible and thermal images. In: IEEE International Conference on Computational Intelligence for Homeland Security and Personal Safety (2006)
128. Nanda, H., Davis, L.: Probabilistic template based pedestrian detection in infrared videos. In: IEEE Intelligent Vehicle Symposium, (2002)
129. Neagoe, V.E., Ropot, A.D., Mugioiu, A.C.: Real time face recognition using decision fusion of neural classifiers in the visible and thermal infrared spectrum. In: IEEE Conference on Advanced Video and Signal Based Surveillance (2007)
130. Ng, Y.M.H., Yu, M., Huang, Y., Du, R.: Diagnosis of sheet metal stamping processes based on 3-D thermal energy distribution. IEEE Transactions on Automation Science and Engineering **4**(1), 22–30 (2007)
131. Ó Conaire, C., Cooke, E., O'Connor, N., Murphy, N., Smeaton, A.: Background modelling in infrared and visible spectrum video for people tracking. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, p. 20 (2005)
132. Ó Conaire, C., Cooke, E., O'Connor, N.E., Murphy, N., Smeaton, A.F.: Fusion of infrared and visible spectrum video for indoor surveillance. 6th International Workshop on Image Analysis for Multimedia Interactive Services (2005)
133. Ó Conaire, C., O'Connor, N., Cooke, E., Smeaton, A.: Comparison of fusion methods for thermo-visual surveillance tracking. In: 9th International Conference on Information Fusion (2006)
134. Ohel, E., Rotman, S.R., Blumberg, D.G., Sagiv, L.: Anomaly gas remote sensing and tracking using a field-portable imaging thermal radiometric spectrometer. In: IEEE 24th Convention of Electrical and Electronics Engineers in Israel (2006)
135. Olmeda, D., de la Escalera, A., Armingol, J.: Contrast invariant features for human detection in far infrared images. In: IEEE Intelligent Vehicles Symposium (2012)
136. Olmeda, D., de la Escalera, A., Armingol, J.M.: Detection and tracking of pedestrians in infrared images. In: 3rd International Conference on Signals, Circuits and Systems (2009)
137. Padole, C.N., Alexandre, L.A.: Motion based particle filter for human tracking with thermal imaging. In: 3rd International Conference on Emerging Trends in Engineering and Technology (2010)
138. Padole, C.N., Alexandre, L.A.: Wigner distribution based motion tracking of human beings using thermal imaging. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2010)

139. Panasonic: Infrared array sonsor: Grid-eye (2013). URL http://pewa.panasonic.com/components/built-in-sensors/infrared-array-sensors/grid-eye/
140. Paugam, R., Wooster, M., Roberts, G.: Use of handheld thermal imager data for airborne mapping of fire radiative power and energy and flame front rate of spread. IEEE Transactions on Geoscience and Remote Sensing **51**(6), 3385–3399 (2013)
141. Pavlidis, I., Levine, J., Baukol, P.: Thermal image analysis for anxiety detection. In: International Conference on Image Processing (2001)
142. Peregrina-Barreto, H., Morales-Hernandez, L., Rangel-Magdaleno, J., Vazquez-Rodriguez, P.: Thermal image processing for quantitative determination of temperature variations in plantar angiosomes. In: IEEE International Instrumentation and Measurement Technology Conference (2013)
143. Pham, Q.C., Gond, L., Begard, J., Allezard, N., Sayd, P.: Real-time posture analysis in a crowd using thermal imaging. In: IEEE Conference on Computer Vision and Pattern Recognition (2007)
144. Point Grey Research: Stereo vision products (2012). URL http://www.ptgrey.com/products/stereo.asp
145. Pop, F.M., Gordan, M., Florea, C., Vlaicu, A.: Fusion based approach for thermal and visible face recognition under pose and expresivity variation. In: 9th Roedunet International Conference (2010)
146. Prakash, S., Lee, P.Y., Caelli, T., Raupach, T.: Robust thermal camera calibration and 3d mapping of object surface temperatures (2006)
147. Prata, A.J., Bernardo, C.: Retrieval of volcanic ash particle size, mass and optical depth from a ground-based thermal infrared camera. Journal of Volcanology and Geothermal Research **186**(12), 91–107 (2009)
148. Price, J., Maraviglia, C., Seisler, W., Williams, E., Pauli, M.: System capabilities, requirements and design of the GDL gunfire detection and location system. In: International Symposium on Information Theory (2004)
149. Public Laboratory: Thermal photography (2012). URL http://publiclaboratory.org/tool/thermal-photography
150. Qi, H., Diakides, N.A.: Thermal infrared imaging in early breast cancer detection-a survey of recent research. In: 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2003)
151. Ran, Y., Leykin, A., Hammoud, R.: Thermal-visible video fusion for moving target tracking and pedestrian motion analysis and classification. In: Augmented Vision Perception in Infrared, Advances in Pattern Recognition, pp. 349–369. Springer-Verlag, Berlin (2009)
152. Rasmussen, N.D., Morse, B.S., Goodrich, M.A., Eggett, D.: Fused visible and infrared video for use in wilderness search and rescue. In: Workshop on Applications of Computer Vision (2009)
153. Ring, E.F.J., Ammer, K.: Infrared thermal imaging in medicine. Physiological Measurement **33**(3), R33 (2012)
154. Rogler, R.D., Lobl, H., Schmidt, J.: A diagnostic system for live electrical joints in power transmission systems. In: Forty-Second IEEE Holm Conference on Electrical Contacts. Joint with the 18th International Conference on Electrical Contacts (1996)
155. Rudol, P., Doherty, P.: Human body detection and geolocalization for UAV search and rescue missions using color and thermal imagery. In: IEEE Aerospace Conference (2008)
156. San-Biagio, M., Crocco, M., Cristani, M., Martelli, S., Murino, V.: Low-level multimodal integration on riemannian manifolds for automatic pedestrian detection. In: 15th International Conference on Information Fusion (2012)
157. Sandsten, J., Weibring, P., Edner, H., Svanberg, S.: Real-time gas-correlation imaging employing thermal background radiation. Opt. Express **6**(4), 92–103 (2000)
158. Schweiger, R., Franz, S., Lohlein, O., Ritter, W., Kallhammer, J.E., Franks, J., Krekels, T.: Sensor fusion to enable next generation low cost night vision systems. Optical Sensing and Detection **7726**(1), 772,610–772,620 (2010)
159. Serway, R.A., Jewett, J.W.: Physics for Scientists and Engineers with Modern Physics, sixth edn. Brooks/Cole—Thomson Learning (2004)
160. Shah, P., Merchant, S.N., Desai, U.B.: Fusion of surveillance images in infrared and visible band using curvelet, wavelet and wavelet packet transform. International Journal of Wavelets, Multiresolution and Information Processing **08**(02), 271–292 (2010)
161. Siegel, R.: Land mine detection. IEEE Instrumentation Measurement Magazine **5**(4), 22–28 (2002)
162. Sirmacek, B., Hoegner, L., Stilla, U.: Detection of windows and doors from thermal images by grouping geometrical features. In: Joint Urban Remote Sensing Event (2011)
163. Sissinto, P., Ladeji-Osias, J.: Fusion of infrared and visible images using empirical mode decomposition and spatial opponent processing. In: IEEE Applied Imagery Pattern Recognition Workshop (2011)
164. Sixsmith, A., Johnson, N.: A smart sensor to detect the falls of the elderly. IEEE Pervasive Computing **3**(2), 42–47 (2004)
165. Skoglar, P., Orguner, U., Törnqvist, D., Gustafsson, F.: Pedestrian tracking with an infrared sensor using road network information. EURASIP Journal on Advances in Signal Processing **2012**, 1–18 (2012)
166. Socolinsky, D.A., Selinger, A.: Thermal face recognition over time. In: 17th International Conference on Pattern Recognition (2004)
167. Socolinsky, D.A., Selinger, A., Neuheisel, J.D.: Face recognition with visible and thermal infrared imagery. Computer Vision and Image Understanding **91**(12), 72–114 (2003)
168. Socolinsky, D.A., Wolff, L.B., Neuheisel, J.D., Eveland, C.K.: Illumination invariant face recognition using thermal infrared imagery. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2001)
169. Sonn, S., Bilodeau, G.A., Galinier, P.: Fast and accurate registration of visible and infrared videos. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops (2013)
170. Sony Electronics Inc.: XC-E150 Near Infrared camera (2012). URL http://pro.sony.com/bbsc/ssr/cat-recmedia/cat-recmediadtwo/product-XCEI50/
171. St-Laurent, L., Maldague, X., Prevost, D.: Combination of colour and thermal sensors for enhanced object detection. In: 10th International Conference on Information Fusion (2007)
172. Steen, K.A., Villa-Henriksen, A., Therkildsen, O.R., Karstoft, H., Green, O.: Automatic detection of animals using thermal imaging. In: International Conference on Agricultural Engineering (2012)
173. Suard, F., Rakotomamonjy, A., Bensrhair, A., Broggi, A.: Pedestrian detection using infrared images and histograms of oriented gradients. In: IEEE Intelligent Vehicles Symposium (2006)

174. Szwoch, G., Szczodrak, M.: Detection of moving objects in images combined from video and thermal cameras. In: Multimedia Communications, Services and Security, *Communications in Computer and Information Science*, vol. 368, pp. 262–272 (2013)
175. Toet, A., Hogervorst, M.A.: Towards an optimal color representation for multiband nightvision systems. In: 12th International Conference on Information Fusion (2009)
176. Torabi, A., Mass, G., Bilodeau, G.A.: An iterative integrated framework for thermalvisible image registration, sensor fusion, and people tracking for video surveillance applications. Computer Vision and Image Understanding **116**(2), 210–221 (2012)
177. Torresan, H., Turgeon, B., Ibarra-castanedo, C., Hébert, P., Maldague, X.: Advanced surveillance systems: Combining video and thermal imagery for pedestrian detection. In: In Proc. of SPIE, Thermosense XXVI, volume 5405 of SPIE, pp. 506–515 (2004)
178. Treptow, A., Cielniak, G., Duckett, T.: Real-time people tracking for mobile robots using thermal vision. Robotics and Autonomous Systems **54**(9), 729–739 (2006)
179. Vadivambal, R., Jayas, D.: Applications of thermal imaging in agriculture and food industry—A review. Food and Bioprocess Technology **4**, 186–199 (2011)
180. Vidas, S., Lakemond, R., Denman, S., Fookes, C., Sridharan, S., Wark, T.: A mask-based approach for the geometric calibration of thermal-infrared cameras. IEEE Transactions on Instrumentation and Measurement **61**(6), 1625–1635 (2012)
181. Vollmer, M., Möllmann, K.P.: Infrared Thermal Imaging—Fundamentals, Research and Applications. Wiley-VCH (2010)
182. Walczyk, R., Armitage, A., Binnie, T.D.: An embedded real-time pedestrian detection system using an infrared camera. In: IET Irish Signals and Systems Conference (2009)
183. Wang, R., Wang, G., Chen, Z., Liu, J., Shi, Y.: An improved method of identification based on thermal palm vein image. In: Neural Information Processing, *Lecture Notes in Computer Science*, vol. 7664, pp. 18–24. Springer Berlin Heidelberg (2012)
184. Wang, W., Zhang, J., Shen, C.: Improved human detection and classification in thermal images. In: 17th IEEE International Conference on Image Processing (2010)
185. Warriss, P.D., Pope, S.J., Brown, S.N., Wilkins, L.J., Knowles, T.G.: Estimating the body temperature of groups of pigs by thermal imaging. Veterinary Record **158**, 331–334 (2006)
186. Wasaki, K., Shimoi, N., Takita, Y., Kawamoto, P.N.: A smart sensing method for mine detection using time difference IR images. In: International Conference on Multisensor Fusion and Integration for Intelligent Systems (2001)
187. Wikipedia: Atmospheric transmittance (2006). URL http://en.wikipedia.org/wiki/File:Atmosfaerisk_spredning.gif
188. Wolff, L., Socolinsky, D., Eveland, C.: Face recognition in the thermal infrared. In: Computer Vision Beyond the Visible Spectrum, Advances in Pattern Recognition, pp. 167–191. Springer-Verlag, Berlin (2005)
189. Wong, W.K., Chew, Z.Y., Loo, C.K., Lim, W.S.: An effective trespasser detection system using thermal camera. In: Second International Conference on Computer Research and Development (2010)
190. Wong, W.K., Lim, H.L., Loo, C.K., Lim, W.S.: Home alone faint detection surveillance system using thermal camera. In: Second International Conference on Computer Research and Development (2010)
191. Wong, W.K., Tan, P.N., Loo, C.K., Lim, W.S.: An effective surveillance system using thermal camera. In: International Conference on Signal Acquisition and Processing (2009)
192. Wu, S., Jiang, L., Xie, S., Yeo, A.C.B.: A robust method for detecting facial orientation in infrared images. Pattern Recognition **39**(2), 303–309 (2006)
193. Xu, F., Liu, X., Fujimura, K.: Pedestrian detection and tracking with night vision. IEEE Transactions on Intelligent Transportation Systems **6**(1), 63–71 (2005)
194. Yanmaz, L.E., Okumus, Z., Dogan, E.: Instrumentation of thermography and its applications in horses. Journal of Animal and Veterinary Advances **6**(7), 858–862 (2007)
195. Yiu-Ming, Ng, H., Du, R.: Acquisition of 3d surface temperature distribution of a car body. In: IEEE International Conference on Information Acquisition (2005)
196. Yoshitomi, Y., Miyaura, T., Tomita, S., Kimura, S.: Face identification using thermal image processing. In: 6th IEEE International Workshop on Robot and Human Communication (1997)
197. Yoshitomi, Y., Miyawaki, N., Tomita, S., Kimura, S.: Facial expression recognition using thermal image processing and neural network. In: 6th IEEE International Workshop on Robot and Human Communication (1997)
198. Yu, X., Chua, W.K., Dong, L., Hoe, K.E., Li, L.: Head pose estimation in thermal images for human and robot interaction. In: 2nd International Conference on Industrial Mechatronics and Automation (2010)
199. Zhang, L., Wu, B., Nevatia, R.: Pedestrian detection in infrared images based on local shape features. In: IEEE Conference on Computer Vision and Pattern Recognition (2007)
200. Zhao, J., Cheung, S.c.S.: Human segmentation by fusing visible-light and thermal imaginary. In: IEEE 12th International Conference on Computer Vision Workshops (2009)
201. Zhou, D., Dillon, M., Kwon, E.: Tracking-based deer vehicle collision detection using thermal imaging. In: IEEE International Conference on Robotics and Biomimetics (2009)
202. Zhou, Y., Tsiamyrtzis, P., Lindner, P., Timofeyev, I., Pavlidis, I.: Spatiotemporal smoothing as a basis for facial tissue tracking in thermal imaging. IEEE Transactions on Biomedical Engineering **60**(5), 1280–1289 (2013)
203. Zin, T.T., Takahashi, H., Hama, H.: Robust person detection using far infrared camera for image fusion. In: Second International Conference on Innovative Computing, Information and Control (2007)
204. Zin, T.T., Takahashi, H., Toriu, T., Hama, H.: Fusion of infrared and visible images for robust person detection. In: Image Fusion, pp. 239–264. InTech (2011)
205. Zou, X., Kittler, J., Messer, K.: Illumination invariant face recognition: A survey. In: First IEEE International Conference on Biometrics: Theory, Applications, and Systems (2007)