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Wearable Multispectral Imaging and Telemetry at Edge

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Abstract

We present a head-mounted holographic display system for thermographic image overlay, biometric sensing, and wireless telemetry. The system is lightweight and reconfigurable for multiple field applications, including object contour detection and enhancement, breathing rate detection, and telemetry over a mobile phone for peer-to-peer communication and incident command dashboard. Due to the constraints of the limited computing power of an embedded system, we developed a lightweight image processing algorithm for edge detection and breath rate detection, as well as an image compression codec. The system can be integrated into a helmet or personal protection equipment such as a face shield or goggles. It can be applied to firefighting, medical emergency response, and other first-response operations. Finally, we present a case study of "Cold Trailing" for forest fire containment.

Introduction

Telemetry is a critical component to allow emergency response teams to sense the situation around them. Existing augmented reality (AR) interfaces [12-15] are not built for extreme environments such as smoke, dark, noisy, and poor communication conditions. We need affordable AR platforms that can survive extreme environments and provide on-demand information for first responders and command posts.

In this study we develop a head-mounted holographic display system for thermographic image overlay, biometric sensing, and wireless telemetry. The system is lightweight and reconfigurable for multiple field applications, including object contour detection and enhancement, breathing rate detection, and telemetry over a mobile phone for peer-to-peer communication and incident commanding dashboard. Due to the constraints of the limited computing power of an embedded system, we developed a lightweight image processing algorithm for edge detection and breath rate detection, as well as an image compression codec. The system can be integrated into a helmet or personal protection equipment such as a face shield or goggles. It can be applied to firefighting, medical emergency response, and other first-response operations. Finally, we present a case study of "Cold Trailing" for forest fire containment in the wild.

The Multispectral Imaging Helmet

The spectral imaging and telemetry helmet system contains a microprocessor, with a microphone, Wi-Fi, and Bluetooth. We identify it as "multispectral" because of its capability for integrating and overlaying thermal, visible, and other available electromagnetic spectrum images, as well as provision for future integration and overlaying of non-electromagnetic imaging modalities, e.g., ultrasound. The microprocessor is connected to basic sensors for firefighters: thermal camera, a 10-DOF IMU motion sensors, and tactile button. The system can be expanded with add-on sensors such as 1-dimensional laser distance measurement sensor (1D-LIDAR), depth sensor, stereo vision cameras, and GPS, and a more powerful embedded computer. Figure 1 shows the thermal imaging and telemetry helmet for firefighters.

Figure 1. The thermal imaging and telemetry helmet for firefighters.

Software Architecture

The thermal imaging module provides a real-time thermal image overlay to help first responders navigate environments with limited visibility. The helmet's tactile button is used to cycle between states. Pseudocode for the basic demo software is below. The IMU provides direction and altitude information. The first step in the demo is calibrating this unit. We tried to use runtime calibration, but that delivers less accurate results than offline calibration. Thus our protocol includes the calibration step of briefly rotating the helmet in all three natural planes. After this stage the program displays a screen of current IMU information about position and direction.

```
Start
Initialization for sensors and calibration
Read IMU data
Do While checking button status
   Overlay Heading, Altitude, and Temperature readings
   Demo 1: Display raw thermal video
   Demo 2: Overlay thermal video on the target (zoomed)
   Demo 3: Overlay edge of thermal image on the target
End While
```

The thermal imaging demonstration is the hyper-reality overlay as shown in Figure 2. It displays a real time thermal image with the heading “H”, the temperature “T”, and the altitude “A”. We included four modes for displaying the thermal image with a normal grayscale thermal image, a view using Canny edge detection, and a zoom option for both to magnify far away objects. After the initial IMU calibration, the demo cycles between these viewing modes when the button is pressed.

Figure 2. The overlaid thermal image (left) and contour (right) on the head-up display in the helmet.

Telemetry from a Wearable Computer

Telemetry is critical to many first responders for transmitting the real-time sensory data from the field to the commending center. The challenge is how to transmit the critical data from a wearable computer over an unstable and narrow bandwidth network.

Typically, mobile videos can be transmitted over Wi-Fi or cellular data networks. However, many wearable computers have very limited computational power for video encoding and decoding algorithms. For example, TCP/IP protocol performs rigid error checking and resending that many embedded systems cannot afford. The UDP protocol on the other hand, requires less error-checking and less onboard computation, which is a preferred alternative to our telemetry process.

On top of the transmission protocol, we have to compress and decode the thermal video in real-time without cost too much computing resources from the wearable computer. There are many image compression algorithms such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT), et al. But they are computationally expensive unless special chips are provided. In our project, we use the Least Significant Bit (LSB) compression method [17].

A pixel in an image normally contains either 8-bits or 24-bits of information. The 8-bit resolution is good enough for representing gray-scale images, which has 255 shades of gray. The 24-bits resolution is appropriate for representing color images, which consist of red, green, and blue (RGB) channels with 8-bit resolution for each, which can represent up to 16,581,375 colors.

For example, if we take one pixel out of a gray-scale image. It is an 8-digit number in the binary form: 11000011. We can break the number into two parts: the left most four digits are the most significant bits (MSB); and the right most four digits are the least significant bits (LSB). Any changes in the most significant bits will make a noticeable difference. On the other hand, any changes in the least significant bits won’t make a perceptively noticeable difference, so won’t have much visual impact.

How do we measure the image distortion due to the video compression? For computerized image quality evaluation, we can view the compressed image as a noisy image and use the Peak Signal to Noise Ratio (PSNR) for an objective measurement. Assume the maximum possible pixel value of the cover image is MAX. When the pixels are represented in 8 bits per sample, it is 255. Also assume we have the mean squared errors (MSE) of pixels of the cover image and the resultant steganographic image. We have,

$$PSNR = 10\log_{10}\frac{MAX^2}{MSE}$$

PSNR models the human eyes’ logarithmic response to the visual differences between the two images. It has been widely used for measuring the performance of image compression algorithms. The higher the PSNR value the better the image quality. Typical values for the PSNR in video compression are between 30 and 50 dB, provided the bit depth is 8 bits. For 16-bit data typical values are between 60 and 80 dB. Acceptable values for wireless transmission quality loss should be between 20 and 25 dB. Therefore, the PSNR of the compressed image cannot be lower than the typical range to avoid noticeable imagery distortion [17].

Thermal Calibration

The thermal camera, FLIR Lepton 3.5, has a stated accuracy of +/- 9 F (5 C) which is obviously not suitable for fever tracking where a difference of just 1 F (0.6 C) could be critical. Measurements from the thermal camera were recorded for multiple water sources and compared with a digital thermometer. It was found that the thermal camera had an offset value which would change with each Flat Field Correction (FFC) which is an offset calibration to compensate for errors that build up over time in the camera.

After correcting this offset value by manual or automated methods, the accuracy of the thermal chip is much improved. The temperature accuracy analysis is carried out and an accuracy of +/- 1 F (0.6 C), an interquartile range of 0.5 F (0.3 C), and a standard deviation of 0.44 F (0.24 C).

As the ambient temperature of the room changes the output of the thermal camera changes, even if we are measuring a fixed point with a constant temperature. Also the thermal camera performing an FCC will change the output temperature from the thermal camera. By measuring the temperature of a point in the background manually, in this case with a thermal measurement gun, we can then compare the temperature of the point from the thermometer and the thermal camera and generate an offset value to apply to the frame.

The next step could include a fixed point with a measuring device that could communicate with the thermal imaging system so not to have to rely on manual measurements.

Initial prototyping of the system was done at a lower resolution to optimize for speed. At 480p for the RGB frame the face detection could operate at a maximum distance of 8 feet (2.4 m). After optimizing the software the fever screening system could run at high speed at a higher resolution of 720p, extending the distance of face detection to 13 feet (4.0 m).

The distance between the subject and the thermal camera has an effect on measured temperature. We can correct for this effect using the distance sensor. We standardize by always measuring to the subject’s forehead. The perturbation is due to atmospheric attenuation between the thermal imaging camera and the human subject. We carried out tests to measure the change in measured temperature of a subject as they walked towards the thermal camera, with their distance to the camera calculated by tracking the target in the depth image. The results are shown in Figure 3. For the distance of 1 - 13 feet (0.3 – 4.0 m) the measured temperature declines more rapidly at short distances and less rapidly at larger distances, as shown in blue. This is consistent with the expected Beer-Lambert

Law of exponential attenuation with distance. By applying the measured correction to the raw temperature measurement the adjusted temperature accurately describes the actual temperature of the measured subject independent of distance over a useful distance range. The corrected temperature, shown in orange, is now essentially flat. Random variations around this corrected temperature are likely due to the tracked point on the forehead changing slightly when the subject walks towards the thermal camera, and to small inaccuracies inherent to the camera.

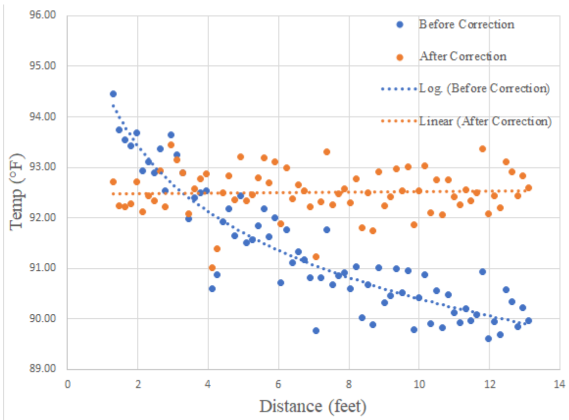

Figure 3. Temperature vs distance from thermal camera.

Tracking Camera Motion

We tested the Scale-Invariant Feature Transform (SIFT) key point-based tracking with a single camera on the mobile phone Samsung S6. The number of matched tracking points depends on the texture features in the scene and motion. The algorithm requires a minimum number of matched points in individual frames. When the camera turns around, old key points may be lost, and new key points have to be added automatically. This demands fast frame capture and computation in order to track properly. We also tried to find the key points from the thermal imaging frames (160 x 120 pixels). The algorithm did not find any key points. We have to find better ways to extract tracking points. For example, corner detection instead of SIFT key points and incorporating IMU sensors to understand the pose and dynamics of the camera.

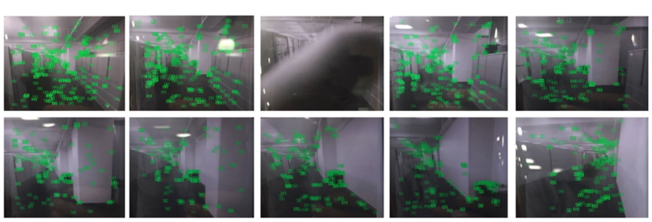

Figure 4. SIFT key point tracking while the camera moved around the office. Note the blackout on the 3rd image.

Tracking Corners and Edges

We tried to extract corner feature points and edges from the FLIR Lepton 3.5 thermal images at 160 x 120 pixels resolution. The detection algorithm is based on the Harris filter method. The results appear reasonable. See Figure 5 and 6. The Lepton 3.5 camera had some dead pixels on the horizontal line of the middle of the image. They were mistaken as corners. This error can be reduced by replacing the camera or linear interpolation in software. We aim to use corners to replace the SIFT key points. We can track those corners for localization and landmark detection. We also use the Canny edge detection algorithm to extract edge contours. Edge tracking may be used for tracking directly, but it can be used for highlighting objects on the see-through HUD. It can be helpful in smoky environments. Contour rendering can also be helpful if the line color indicates temperature or other physical properties.

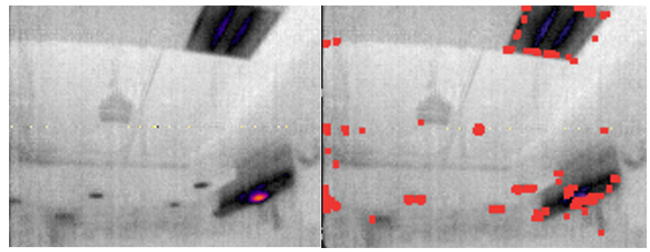

Figure 5. Tracking corners from thermal images.

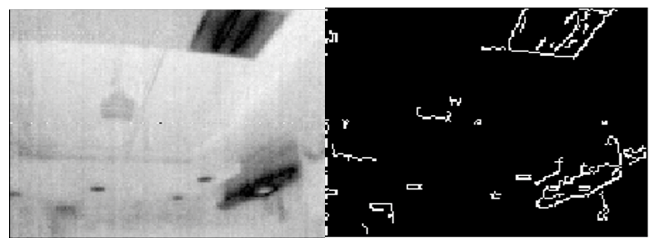

Figure 6. Tracking edges from thermal images.

Tracking Gloves in Thermograph

We experimented with thermal imaging-based glove tracking. Due to the thermal isolation of the firefighter's gloves, it is challenging to detect the temperature difference between the glove and the environment. So we attached a thermal reflective tag on the glove. From the thermograph, the reflective tag exhibits easy-to-track high contrast. We also tested thermal reflective tags on fire alarms and door handles. We found that it is possible to spray thermal reflective paint onto a glove to make it easier to track in thermal videos. Figure 7 shows the glove with the thermal reflective tag and the result on the thermal image.

Figure 7. Thermal Reflectors for the Glove (left) and Thermal Imaging.

Breath Rate Detection

Respiratory rate (RR) or breath rate (BR) is essential data in determining emergency medical responses. There are many contact-based respiratory rate sensors or blood oxygen-based sensors. Thermal imaging, on the other hand, provides remote sensing capability for first responders or drones in the field for triage purposes. When we breath, the air temperature from the nasal area changes correspondingly, which change is reflected in the pixel values around the nose and perhaps the mouth. In our system, we track the nasal area with a bounding box. The wearable computer calculates the intensity variations in the nasal area and summarizes the respiratory rate or breath rate within 30 or 60 seconds. Figure 8 shows the first responder aims the thermal camera at the nasal area of the simulated disaster victim (left) and the overlaid breath rate and dynamic patterns on the glass attached to the helmet (right). In order to maximize the sensitivity of the pixel value variation in the nasal area, we place the thermal camera below the nose so that the dynamics can be more visible.

Table 1 shows the sample of experimental results at the lab and a bar with 5 subjects, including 4 male and 1 female. The average accuracy is 85.7%, assuming the respiratory rate is consistent throughout the measurement period.

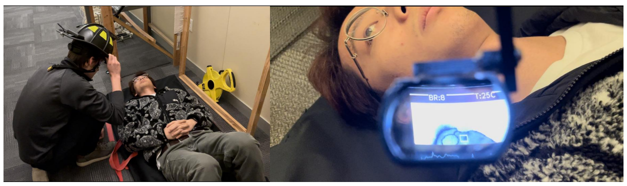

Figure 8. The first responder aims at the nasal region of the victim (left) and the overlaid breath rate and dynamic pattern on the glass (right).

Table 1. Experimental results at the lab with 5 subjects (breath per minute)

Self-Count	12	14	22	18	13
Thermal Data	14	17	24	15	12

Cold Trailing

Wildfire fighting is a growing challenge as global warming accelerates. Normally, after a wildfire, firefighters need to survey the ground temperature of the burnt field to prevent returning fires, called "Cold Trailing" according to the Department of Agriculture of USA. The prevailing survey method is to touch the ground with a bare hand, which is neither safe nor inefficient.

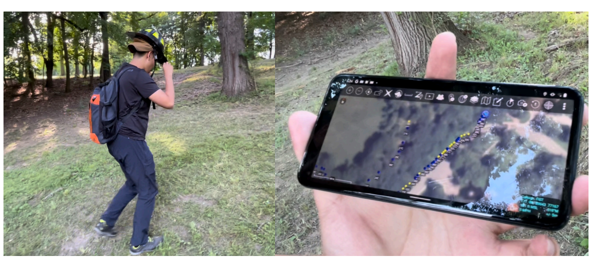

Figure 9. The firefighter walks in the field to take the ground temperature (left) and the cellphone maps the ground temperature data and transmits it to the command center (right).

In this study we use the thermal imaging sensor to measure the ground temperature by pressing a button or speaking a verbal command into the microphone on the helmet. The onboard computer sends the temperature data to the firefighter's mobile phone via Bluetooth, and the mobile phone maps the temperature data in colored dots with GPS coordinates. In parallel, the mobile phone app sends the Cold Trailing data to the Incident Command Center. We tested the wearable thermal imaging and telemetry system at Schenley Park, Pittsburgh, Pennsylvania, through a wooded area. We recorded a data point every 5 feet (1.5 m) along the path. The map reflects the Cold Trailing data in real-time. See Figure 9.

Conclusions

In this study we develop a head-mounted holographic display system for thermographic image overlay, biometric sensing, and wireless telemetry. The system is lightweight and reconfigurable for multiple field applications, including object contour detection and enhancement, breathing rate detection, and telemetry over a mobile phone for peer-to-peer communication and incident command dashboard.

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The wearable thermal imaging and telemetry system is still in its early stage. We need further improvement of the accuracy, robustness, and affordability of the system.

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