3D Thermal Monitoring and Measurement using Smart-phone and IR Thermal Sensor

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Abstract: Continuous and on the fly heat monitoring in industries like manufacturing and chemical is of compelling research nowadays. The recent advancement in IR thermal sensors unfold the possibilities to fuse the thermal information with other low cost sensor (like optical camera) to perform area or volumetric heat measurement of any heated object. Recent development of affordable handheld mobile thermal sensor as a smart-phone attachment by FLIR encouraged the researcher to develop thermal monitoring system as smart-phone application. In pursuit of this goal we present a light weight system with a combination of optical and thermal sensors to create a thermal dense 3D model along with area/volume measurement of the heated zones using smart-phone. Our proposed pipeline captures RGB and thermal images simultaneously using FLIR thermal attachment. Estimates the poses for RGB and depth images, 3D models are generated by tracking the features from RGB images. Back-projection is used to colour the 3D points to represent both in RGB as well as an estimated surface temperature. The final output of the system is the detected hot region with area/volumetric measurement. Experimental results demonstrate that the cost effective system is capable to measure hot areas accurately and usable in everyday life.

1 INTRODUCTION

Unobtrusive heat measurement and monitoring is well accepted in manufacturing, chemical, automobile, construction industries. Conventional industrial thermal cameras are still not in affordable range for everyday life usage. Conventional thermography for energy measurement and non-invasive assessments relies on 2D thermal images, which have significant limitations like lack of information on the shape and geometry or location of the object of interest in the scene. So there is growing interest on representing the environment in 3D which also integrates the temperature information. The combined information will help to detect the object of interest and volumetric measurement precisely. Autonomous solution is in high demand in the market, especially in industries like manufacturing and chemical and also systems which are usable in everyday life. FLIR lunched an affordable thermal sensor (FLIR, 2014) as smart-phone attachment which manifolds the possibility of monitoring and verification of heated region using such hand held mobile low cost sensors.

We present a cost effective 3D thermal mapping system in contrast of conventional thermal camera without compromising much of qualitative measure. The system is capable of area or volumetric measurement of heat in a continuous and non-invasive way. The proposed system is consists of a hand held smart-phone and a FLIR thermal attachment. FLIR thermal attachment for smart-phone is features enrich product within affordable price compare to costly conventional thermal sensors. FLIR thermal attachment comes with 160x120 thermal resolutions which are further scaled up to VGA resolution using FLIR MSX technology (FLIR, 2014) and it is capable to detect temperatures between -20°C to 120°C with a resolution of 0.1°C. Conventional thermal sensors are more on to measure the heat accurately in a 2D space. The proposed system is capable of generating dense 3D model with thermal annotation for the purpose of further processing and measurement volumetric heat on the fly for everyday usage. The system can be consider as a trade-off with more accurate thermal camera where volumetric heat measurement is more important compare to the

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accuracy of thermal measurement for example sludge-heel formation inside in an oil tank. The proposed system is sub set of much bigger concept presented by P. Deshpande et al., (2015).

The major contributions are:

- Designing a hand-held light weight system for continuous monitoring and measurement of heated zone for everyday usage which can be extend for various industries like oil refinery, automobile industries etc.
- Creating smart-phone application for thermal measurement using FLIR thermal attachment.
- Finding out the heated regions automatically and measurement of heat area or volume accurately in 3 dimensions.

Our entire framework exploits several state-of-the-art algorithms for generating dense 3D environment using IMU sensors. We present experimental results, which prove that proposed system can be utilized in wide range of scenarios. We also evaluate the accuracy of the reconstruction by comparing with the ground truth.

2 STATE OF THE ART

Several studies are performed to explore the potential of 3D thermal mapping and volumetric inspection. The studies are mostly focused on monitoring building power consumption.

ThermalMapper (Borrmann et al., 2012) is a well-known project which uses a terrestrial laser scanner and thermal infrared camera on a wheel robot. The thermal data is kept on projecting onto the 3D model as soon as it is generated by laser scanner. The final result from ThermalMapper is a dense 3D point cloud which can be visualized in both RGB and thermal. Volumetric heat measurement and analysis is not part of the presented system. There is significant cost and mobility difference between the presented systems with our proposed system due to the usage of a light weight (approximately 78 grams) low cost FLIR attachment with smart-phone.

In a recent work Vidas et al., (2013) represent a 3D thermal mapping to monitor building interiors using Microsoft Kinect (Microsoft, 2010) and a thermal camera. In computer vision and robotics, the use of RGBD cameras like Microsoft Kinect facilitates the development of techniques for highly-detailed and spatially-extended reconstructions (Meilland and Comport, 2013; Whelan et al., 2013). Such costly and bulky coupled sensors are capable of reconstructing in real-time (Newcombe et al., 2011), but the use of structured light pattern make the product usage limited within indoor environment and short range measurements. The presented system is limited to present 3 dimensional environments with surface temperature annotation and automatic heat measurement and analysis is out of scope. The dimension, weight and operating environment are the main drawbacks for kinect to be used as a hand-held low cost system. Though active depth sensors have many advantages, there are certain scenario where passive RGB cameras are preferred due to its low power consumption, outdoor capable and form factor. This has motivated many researchers to investigate methods for 3D reconstruction using only passive cameras. So, the stereo approaches are still very popular. There are approaches where binocular vision is used for 3D reconstruction in indoor environment for navigation (Krishnan and Kollipara, 2014). The growing interest of dense reconstruction gave attention in multi-view stereo technique (Seitz et al., 2006; Furukawa et al., 2010) where the computational complexity prevents them to be used as low cost and light weight system.

In a recent work (Pradeep et al., 2013) has described a methodology for marker less tracking and 3D reconstruction in scenes of smaller size using RGB camera sensor. It tracks and re-localizes the camera pose and allows for high quality 3D model reconstruction using a webcam. (Pizzoli et al., 2014) proposed a solution by adapting a probabilistic approach in which depth map is computed by combining Bayesian estimation and convex optimization techniques. These implementations are limited to a small scene reconstruction. These kind of system paired with another thermal camera would generate a clumsy setup and mobility of the entire system would be restricted.

In another work Saha et al., (2014) has presented a system where smart-phone is used as capture device and the entire reconstruction is performed in a backend system. The mobility of the system is main drawback for everyday usage.

Industrial thermal cameras are capable of measuring the temperature accurately from a specified distance and few costly cameras provide dimension of the heated regions in 2 dimensions with a user guided way. FLIR smart-phone thermal attachment is also providing information in 2 dimensional spaces. Volumetric measurements are limited due to 2 dimensions. The cost of thermal cameras is another metric which restrict these products to be used only in industrial segment. FLIR smart-phone thermal attachment brings the opportunity to be used as house hold product for everyday life usage due to the enormous cost reduction, increase mobility for small dimensions and weight and finally user friendly instead of expensive or bulky thermal systems. Automatic Volumetric measurement requires the heat analysis on 3 dimensions, so there are limitations in state of the art for an autonomous affordable system which is capable of area or volumetric measurement of any heated regions in everyday life. We present a smart-phone based framework along with an implemented application for the gap as discussed.

3 FRAMEWORK DESCRIPTION

The block diagram of the entire system is illustrated in figure 1.

3.1 Data Acquisition

We used hand held smart-phone with FLIR thermal attachment for entire data collection and processing. Data collection starts from certain position (according to requirement and camera field of view) and we take this as origin of world coordinate system for entire data collection and calculation. To collect data, we use our two apps in parallel. One app handles the entire image capturing called OptoThermalFLIR App and another app called i-POSE handles the task of recording the IMU data with timestamp.

OptoThermalFLIR app captures optical and thermal image simultaneously at each point and saves with timestamp. i-POSE app runs in background and records the IMU data (accelerometer, magnetometer and gyroscope are used) with timestamp at 200Hz. The timestamp information helps us to map image frame with position from where image has taken. The auto capture of images is controlled using accelerometer sensor. The noisy accelerometer data alone is capable enough to determine the motion status of the phone coarsely. The image capture is triggered only if the smart-phone is detected in stationery condition to avoid motion blur in images. Captured images and pose information are further used for 3D thermal mapping.

3.2 Camera Calibration

The cameras mounted on the FLIR thermal attachment are used in our experiments. Pin-hole camera model (Hartley et al., 2003) is used. The internal calibration process is performed offline using well known checker board methods as described by Zhang (Zhang, 2000).

External calibration are derived from inertial and IMU sensors as described by Bhowmick et al., (2014).

Optical and thermal cameras are apart with fixed distance and they are parallel. So there is a fixed translation between the cameras without any rotation. So the external calibration for the thermal image is derived by adding the fixed translation vector with the calibration matrix of optical camera.

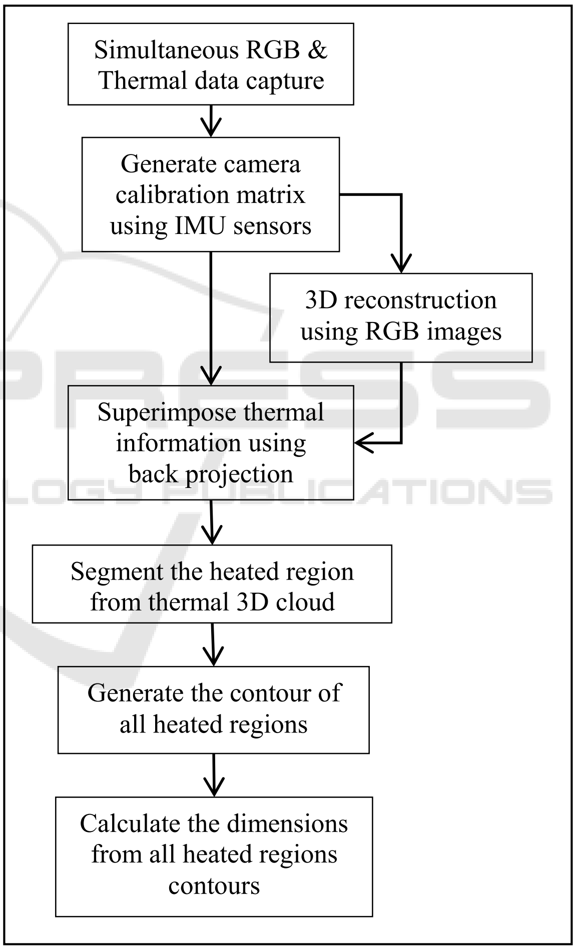

Figure 1: System Workflow.

3.3 Dense Correspondence Estimation

The dense stereo matching is vast and we refer to H. Hirschmuller (Hirschmuller and Scharstein, 2009) for a comparison of all existing methods. In fact, there are few relevant works available on real-time, dense reconstruction using a monocular moving camera.

Motion estimation by means of optical flow is a well-accepted and established methodology for providing dense sampling in time. The predominant way of estimating dense optical flow in today's computer vision literature is by an approach of integrating rich descriptors into the variational optical flow setting as described in T. Brox (Brox and Malik, 2011). The main advantage of the selected approach is the ability to produce better results in a wide range of cases and also for large displacement.

Large displacement optical flow is a variational optimization technique which integrates discrete point matches with continuous energy formulation. The final goal is to find the global minima of the energy and for that the initial guess of the solution has to very close to the global minima. The entire energy is globally minimized and the details of minimization procedure are studied in T. Brox (Brox and Malik, 2011).

The n-view point correspondence generation is carried out using the GPU implementation as described by N. Sundaram (Sundaram et al., 2010). The point trajectories are generated between consecutive frames from the captured images. Optical flow has an effect of accumulating errors in the flow vector. So, a long trajectory suffers from this error and leading to a significant drift. Short trajectories are almost free from the drift error, but the triangulation process suffers due to small base line measurements. Hence, we have chosen consecutive frames that are having base line more than 5 cm and the trajectory length chosen as less than 8.

3.4 Outlier Estimation

Detecting outlier is a very primitive task before doing any further processing with the available information. Outlier detection process is very straight forward and it follows the epipolar constraints (Hartley et al., 2003) as shown in (4).

The main advantage of having accurate camera calibration parameters helps us to generate an accurate fundamental matrix using equation (1) (Hartley et al., 2003).

$$F = K'^{-T}[\mathbf{t}]_x R K^{-1} \tag{1}$$

Where F is the fundamental matrix between an image pair, K and K' correspond to the internal calibration matrix of the image pair, R and t represent the rotation matrix and translation vector of second image with respect to first image.

Rotation matrix R_{ij} between camera pair i and j can be obtained using equation (2) (Hartley et al., 2003) where R_i and R_j denotes the rotation matrix of camera i and j respectively with respect to the global coordinate system.

$$R_{ij} = R_j R_i^{-1} \tag{2}$$

The translation vector t_{ij} between a camera pair i and j is calculated using equation (3) where C_i and C_j denotes the absolute position for camera i and j respectively.

$$\mathbf{t}_{ij} = R_j(C_i - C_j) \tag{3}$$

The corresponding points (x, x') ideally should follow the epipolar constraints as given in equation (4) (Hartley et al., 2003) where F denotes the Fundamental matrix. In reality, the value never becomes zero rather it goes very close to zero. So, any corresponding points in order to be considered as inlier, the value should be below to a threshold. Now, a particular threshold is not suitable for all cases, so there is a requirement of defining a dynamic threshold which can automatically be adjusted depending upon the captured scene. The threshold value is defined as dynamic and it gets calculated based on percentage of rejection.

$$x'^{T} F x = 0 \tag{4}$$

Implemented optical flow algorithm is more error prone towards the image boundaries. Centre of the image is given higher weightage due to the sated reason and pixels are placed near to the image boundaries are removed as outlier.

3.5 3D Model Reconstruction

The 3D model generation is done in form of point cloud. The 3D point cloud is created using triangulation process. The approaches are quite similar as described by Dewangan et al., (2015). Each point is back projected onto the image plane to calculate the back projection error. Any 3D point with back projection error more than 2 pixels is considered as outlier. The camera calibration parameters from IMU sensors and dense point correspondence from optical flow estimation generates an accurate point cloud which does not require any further optimization.

The whole scene reconstruction is done in an incremental way. Images are divided into small sets as mentioned above such that the trajectory length is not more than 8 images. Each subset is merged after triangulation to get the final reconstruction.

3.6 Opto-thermal Mapping

Normally thermal cameras are required to calibrate the intensity in regular interval for correction for a gradual decrease in measured signal accuracy during operation. These operations are known as NUCs (Non-Uniformity Corrections). FLIR thermal attachment is of similar type and required regular calibration.

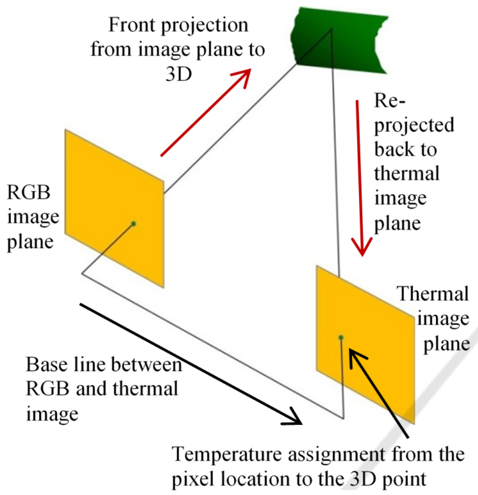

Figure 2: Temperature assignment in 3D model.

One of the great advantages of using FLIR is the placement of optical and thermal camera; both the sensors are very close and reproduce almost similar views. If any 3D point is visible in a RGB image almost all cases it is also visible in the corresponding thermal image. We measure the displacement between these two sensors and incorporate the measurement into calibration. The thermal annotation of every point is almost error free due to very short base line between optical and thermal camera.

Thermal information is assigned on the optical 3D point cloud by applying back projection. Each 3D point from the point cloud is back projected using equation (5) (Hartley et al., 2003) to the corresponding 2D thermal image plane to determine the coordinate on the 2D thermal image plane and determines the temperature from 2D coordinate location of thermal image. The entire process is explained in figure 2.

$$\mathrm{x} = \mathrm{K}(\mathrm{RX} + \mathbf{t}) \tag{5}$$

Where X and x represents the 3D and 2D point respectively.

3.7 Heat Measurement

Thermal 3D point cloud is the representation of thermal profile in 3D space. The visualization is only the annotation of temperature in form of colour as shown in figure 3. The temperature values are the main differentiator in the entire 3D model. Heated regions are segmented using the temperature profile. All segmented point cloud are stored and analysed separately. Point cloud library (PCL) is an open source tool for cloud processing and this is been extensively used in our implementation. Contour of each segmented heat cloud is determined and the area or volume is calculated from the contour.

4 RESULTS

4.1 Test Environment

Our test environment is iPhone 5s with FLIR thermal attachment. The entire framework is implemented and tested as an application.

The accuracy of the proposed system is entirely depends on reconstruction accuracy which is intern dependent on the output of the optical flow. We have incorporated several precaution procedures to make the system robust enough for daily usage. The accuracy of the flow vector is less than a pixel and so the estimated error is in few millimetre ranges for bigger object like car as shown in the example of figure 4. The presented system is probably the first such mobile application as per our knowledge which is capable of measuring area or volume of heat automatically, so unable to benchmark with similar application. Costly thermal cameras are used in industries which are capable of measuring heated area or volume with greater accuracy.

We have tested the application in normal lighting condition in both indoor and outdoor situations and found satisfactory result.

4.2 Outputs

We present two sample heat measurements in different environment to demonstrate the usability.

Figure 3 shows a sample 3D thermal point cloud of a mug containing hot water. The presence of water is only detectable through thermal image. The testing is performed using 11 images with two iterations. The 3D thermal cloud shows the structure of the mug along with the hot region. The idea is to measure the volume of hot water present inside. The mug is segmented by the knowledge of its cylindrical shape. The segmentation finally is used to detect the dimension of the mug. Mostly heated region is extracted from the temperature and the dimension is calculated from 3D structure.

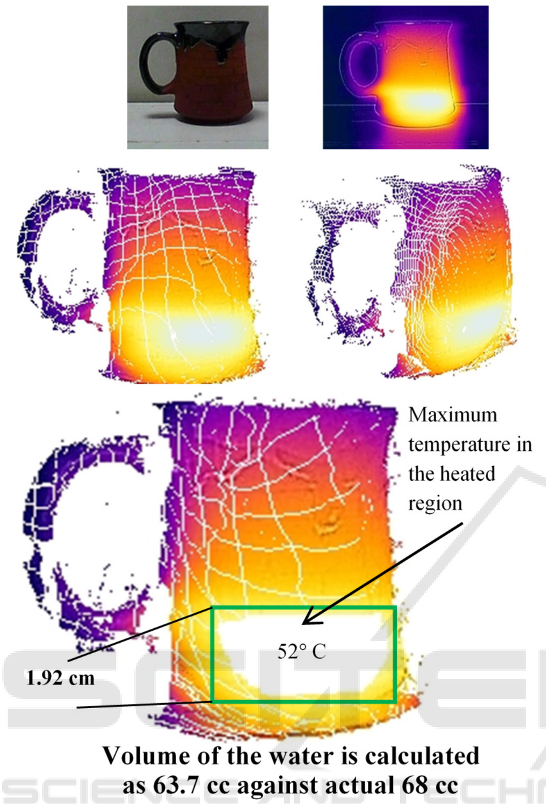

Figure 3: Volumetric Measurement: Top to bottom shows the captured RGB and thermal image, segmented 3D thermal model, detected dimension of the heated region with maximum temperature.

Figure 4 represents thermal profile of a car just after parking in an indoor parking lot. The registration number plates on the images are corrupted intentionally. Thermal profile on the images shows the tires and engine inside the bonnet is the hottest zones as expected. We have measured the surface areas of the heated zones. Any abnormality found in the area of the heated region would eventually help automobile companies to predict or understand the fault in the engine or any other part of a car.

The presented samples show the capabilities to perform a heated area or volumetric analysis in a non-invasive way. Heat measurement is typically depends on the heat flow inside the container and type of material used for the container. We observe the similar characteristics through our experimental experiences. Thermo-flax is typically well known for locking the heat inside the container for longer time so the temperature gradient is not prominent or distinct if we perform experiments with hot water inside of a thermo-flax.

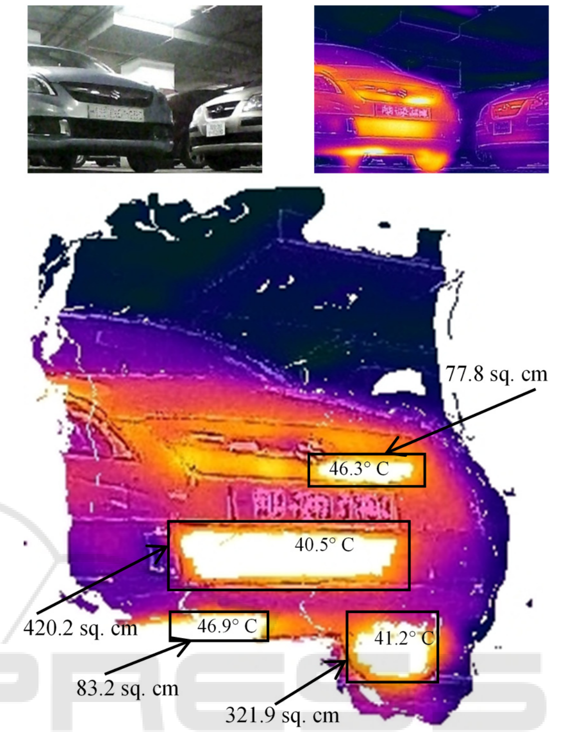

Figure 4: Area Measurement: Top to bottom: RGB and thermal image, detected hot zones with covered area and maximum temperature in each heated region on the thermal 3D model.

4.3 Execution Time

Execution time is highly dependent on 3D reconstruction time and number of images that are used for testing. We could able to process a single image roughly between 2 to 2.5 seconds. The execution time for the samples presented in figure 3 and 4 are 23 seconds and 18 seconds respectively.

5 CONCLUSIONS

We presented an approach for dense 3D thermal mapping for heat monitoring along with area/volumetric heat measurement using smart-phone and FLIR thermal attachment. 3D reconstruction is performed with RGB image and thermal overlapping on 3D model is done to create a 3D thermal structure. Heated regions are segmented and structure of heated regions is analysed to calculate the contours. Area / volume of the heated regions are calculated from the corresponding contours. Our results show the capability of such solution which can be applied in other domain for any specific purpose. The main advantage of such a system is that, it uses only passive sensors for measurement, so it can be deployable in outdoor environment. We also analysed computation time and this shows the solution runs in near real-time.

The heated area or volume measurements with closed container show different heat profile. The heat flow also has a great effect on heat profile. These types of works are considered as further improvement of the entire system.

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