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Super-Resolution Thermal Image Reconstruction

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Abstract— Digital Infrared Thermal Imaging, Thermal Imaging or Thermography, could be the next chapter in safer, more effective screening for cancer, sport injuries including orthopedic issues and more. Unfortunately, thermal image camera resolution is considerably lower than of optical cameras, mostly only 160x120 or 320x240 pixels. The readout durability was still poor and needed improvement. In this paper we introduce a method to enhance image resolution using people tracking scheme. It utilizes a combined input from RGB and thermal cameras. Several thermal frames of low-resolution video may be combined using super-resolution techniques to produce a single still image whose resolution is significantly higher than that of any single frame of the original video. These patterns give us improved information on what is occurring in body's systems and organs.

Keywords- thermography;super-resolution;people tracking.

I. INTRODUCTION (HEADING 1)

A thermal camera, sometimes called a FLIR Forward Looking InfraRed), or an infrared camera less distinctively, is a device that captures an image using infrared radiation, similar to a common camera that forms an image using visible light. Instead of the 450–750 nanometer range of the visible light camera, infrared cameras operate in wavelengths as long as 14,000 nm (14 µm). Thermal imaging photography finds many other applications. For example, firefighters use it to see through smoke, find persons, and localize hotspots of fires. With thermal imaging, power line maintenance technicians locate overheating joints and parts, a telltale sign of their failure, to eliminate potential hazards. Some physiological activities, principally responses, in human beings and other warm-blooded animals can also be monitored with thermographic imaging. Cooled infrared capturing devices can also be found at most major astronomy research telescopes.

Medical Digital Infrared Thermal Imaging is a noninvasive diagnostic technique that allows the doctor to visualize and quantify changes in skin surface temperature. An infrared scanning device is used to convert infrared radiation emitted from the human being body into electrical impulses that are visualized in color on a monitor. This visual image graphically draws the body temperature and is referred to as a thermogram. The spectrum of colors indicate an increase or decrease in the amount of infrared radiation being emitted from the body surface. Since there is a high degree of thermal symmetry in the normal body, subtle abnormal temperature asymmetry can be easily identified.

However, due to camera technology limitations, infrared images usually have lower spatial resolution (fewer pixels) and less sensitivity than visible ones.

Demand for sharpened thermal images drives our research into super-resolution image reconstruction techniques.

Moreover, including these inherent limitations, infrared images do not give as much information as visible ones about objects. This aspect may impair the fact that there is no spectral information in infrared images as there is only one sensor, compared to the three-channel RGB sensor arrangement in visible cameras, and this may lead to some problems in the tracking algorithms. Human motion tracking based on the input from RGB camera already has been producing impressive results for the in-door scenes with the constant illumination and steady backgrounds. However, scenes with significant background clutter due to illumination changes, still appear to be challenging to handle using inputs from a conventional CCD camera. In our work we extend a method of utilizing an additional source of information - a thermal camera/sensor [7] which produces for each pixel a gray scale mapping of the infrared radiation at the corresponding location. The thermal radiation propagates along the tissue by thermal conduction reaching the medium's surface. The surface temperature distribution is acquired by a thermal camera and can be analyzed to reconstruct nanoparticles temperature and location within the tissue.

We describe a super-resolution method for images containing tissues motion. The motion information is evaluated by a nested motion trajectories scheme. First of all, human beings are tracked and their multiple moving segments are isolated using the segmentation algorithm. The motion trajectory models may be characterized by parametric model, such as affine transformations. In other words, such extracted image parts are related by coherent relative, global, locally constant parametric motion vector. Such approach allowed us to think about dynamic scenes as if they were static. Very high accuracy parametric motion estimation and simultaneous segmentation of the motion field is realized by 3D orientation tensors with respect to the affine motion model. The super-resolution introductory processing part to be presented consists of: estimation of 3D orientation tensors, estimation of motion models parameters, and simultaneous segmentation of the motion field, respectively. The algorithm is a generalized version of that of Irani and Peleg's one.

II. TRACKING [7]

The tracking system to operate in a double sensor camera setup, assuming one of the cameras can sense in the thermal part of the spectrum and is calibrated to provide the view matching that of the CCD camera. Also we assume that the location of the floor plane in the capturing video sequence is established, either by supervised or automated calibration methods. The goal of the tracking system is as follows: first effort to employ all available information to achieve the noise free "blob-map" and second, subsequently use the blob-map to perform reliable people tracking to minimize two types of tracking errors—falsely detected people and people missed by the system. This algorithm segments foreground regions out of each frame by using a dynamically adapting background model presented here (see Fig. 1). Because each foreground region could contain multiple people, some hypothesized number of human bodies within each such region by using the head-candidate selection algorithm is assumed. The head is chosen as the most distinguishable and pronounced part of the human body, particularly when observing the scene with a highly elevated monocular camera. As the next step, the system [7] constructs a Bayesian inference model, based on the a priori knowledge of the human parameters and scene layout and geometry. Observations of the body appearances at each frame are a second driving force in the probabilistic scheme. The tracking algorithm has been utilized as human beings isolation module. Such prepared video sequence is then combined via super-resolution thermal image resolution algorithm.

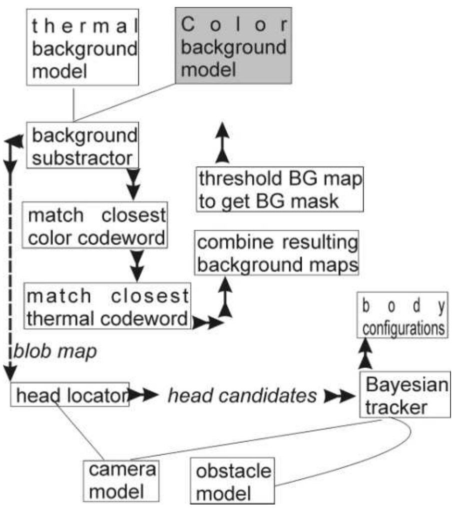

Figure 1. The tracking scheme.

III. SUPER-RESOLUTION THERMAL IMAGE RECONSTRUCTION

Being accurate and powerful, the iterative backprojection SR algorithm [1] have some drawbacks, e.g. only globally static scenes may be processed. Then, if we want to apply the IBP scheme directly, images or video frames should be segmented into areas with uniform motion. We have devised such segmentation scheme for coherent tissues motion areas [4], see Figure 2.

A. *Simultaneous segmentation and velocity estimation*

For best results, estimation of affine motion field should be done over a region with coherent motion. In [4] authors proposed a different approach, weighted neighbourhoods around each pixel have been interpreted as regions. In this section an efficient algorithm for simultaneous segmentation and velocity estimation, given an orientation tensor field for only one frame, is presented. The task for the segmentation is to partition the image into a set of disjoint regions, so that each region is characterized by a uniform motion described by affine model. In this section a region R is defined to be a nonempty, connected set of pixels. The segmentation algorithm has been based on a competitive region growing approach [4].

A cost function $C_R(x)$ is associated with each region defined for all pixels in the image. Regions are growing by adding one pixel at a time. To preserve connectivity the new pixel must be closest to the region, and to preserve disjointedness it must not be already assigned to some other region. The new pixel should be as "inexpensive" as it is possible. The details are as follows. Let the border ΔR of region *R* be the set of unassigned pixels in the image which are adjacent to some pixel in *R*. For each region *R*, the possible candidate, *N(R)*, to be added to the region is the least expensive pixel bordering to *R*, i.e. $N(R) = \arg\min_{x\in\Delta R} C_R(x)$

The corresponding minimum cost for adding the candidate to the region is denoted $C_{\min}(R)$. In the case of an empty border, N(R) is undefined and $C_{\min}(R)$ is infinite. Assuming that a number of regions $\{R_n\}$ have been obtained in some way, the rest of the image is partitioned as follows.

1. Find the region R_i for which the cost to add a new pixel is the least, i.e. let $i = \arg\min_n C_{\min}(R_n)$.
2. Add the least expensive pixel $N(R_i)$ to R_i.
3. Repeat first 2 steps until no unassigned pixels remain.

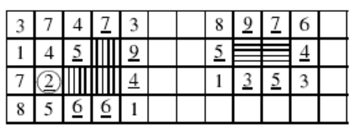

Figure 2. Illustration of the competitive algorithm [4]

Regrowing is performed for one candidate region at a time, which means that there is no competition between regions but rather between pixels. At the beginning the candidate region contains only one point, its starting point, which is also the centre point of the initial rectangle surrounding it. The cost function used is $(\hat{v}T\hat{v})/trT$ where v is the velocity of the candidate region's current motion model. The competitive algorithm is then running until the candidate region has grown to a specified size. This size is called the candidate region size, and is a design parameter of the segmentation algorithm. The result of the regrowing scheme is that the candidate region consists of connected pixels, that are most consistent with the candidate region's motion model. When the candidate region has been regrown, new optimal parameters are computed. Each candidate region is regrown twice [4], a number which seems to be sufficient to obtain reasonably coherent regions. The segmentation algorithm efficiency has been gained by the silhouette contour information. This knowledge comes from thermal image video sequence.

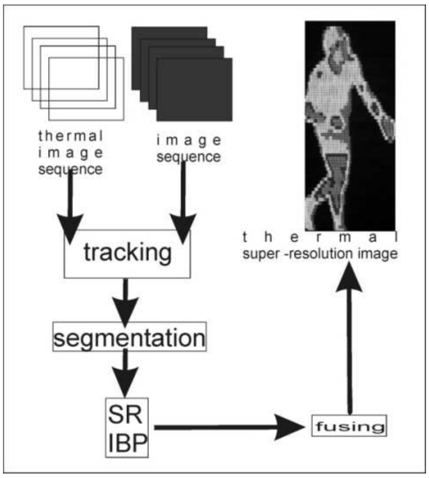

Figure 3. Modified IBP Super-Resolution-Segmentaion diagram

B. *Modified Super-Resolution Image Reconstruction*

Starting with an initial guess f_0 [1] for the high resolution image, the imaging process is simulated to obtain a set of low resolution images $\{g_k^{(0)}\}$ corresponding to the observed input images $\{g_k\}$ If f_0 were the correct high resolution image (1), then the simulated images $\{g_k\}$ should be identical to the observed images. The difference images $(g_k - g_k^{n})$ are used to improve the initial guess by "back projecting" each value in difference images onto its corresponding field in f_0, yielding an improved high resolution image f_1. This process is repeated iteratively to minimize the remaining error. This iterative update scheme can be expressed by:

$$f^{(n+1)} = f^{(n)} + \frac{1}{K}\sum_{k=1}^{K} T_k^{-1}(((g_k - g_k^{(n)})\uparrow s)*p) \tag{1}$$

where K is the number of low resolution images $\uparrow$ arrow an upsampling operator by a factor s and p is a back projection kernel determined by h and Tk. Taking the average of all discrepancies has the effect of reducing noise.

IV. Experiment

In this experiment 5 seconds 160x120 thermal and 30 fps / 720x576 CCD sequences have been captured. Coherent tissues motion has been included. At the beginning human being objects have been tracked. The next step involved thermal image reconstruction procedure from the isolated human beings sub-images.

It is clearly visible that there are many more details in the high-resolution image obtained in this way, see Figure 4.

Figure 4. From left to right: the 160x120 thermal frame, super-resolved thermal frame, CCD camera frame.

V. Conclusion and Future Work

The new thermal image super resolution algorithm, based on dual camera tracking system and tissues movements analysis, has been presented. In general, when applying SR to thermographic we can break down limits on inherent resolution of existing imaging hardware. The same can be told about the proposed algorithm, which in addition does not add significant time to data reconstruction, if compared to the typical image processing procedure. Thus, the proposed technique may find applications in all traffic sport and other analysis system. Moreover, the proposed scheme takes into account tissues movements.

The new technique may also find applications in various image processing applications, excluding a very hard case of curvilinear motion, for instance fine-detailed clouds in the sky [7]. Presented super-resolution scheme may be especially attractive in surveillance, tracking, and many more domains where acquisition of high resolution frames is needed.

One way to increase the accuracy of tracking part is to improve binary foreground map to cover probabilities of each pixel belonging to foreground

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