

“Human Detection with Multiple Cameras Using Background Reduction Technique

Miss.Purnima Bhangale
PG Student,
Department Electronics,
N.M.University,
Jalgaon, Maharashtra,
India.

Miss.Pooja Bhangale
PG Student,
Department Electronics,
B.H.M University,
Aurangabad, Maharashtra,
India.

Prof.V.D.Chaudhari
Professor,
Department Electronics,
N.M.University,
Jalgaon, Maharashtra,
India.

Prof.P.R.Thorat
Professor,
Department Electronics,
B.H.M University,
Aurangabad, Maharashtra,
India.

Abstract:

This paper presents a real-time tracking system to detect and track multiple moving objects on a controlled pan-tilt camera platform. In order to describe the relationship between the targets and camera in this tracking system, the input/output hidden Markov model (HMM) is applied here in the well-defined spherical camera coordinate. Since the detection and tracking for different targets are performed at the same time on a moving camera platform, the detection and tracking processes must be fast and effective. A hybrid detection algorithm which combines the target's color and optical flow information is proposed here. A two layer tracking architecture is then utilized for tracking the detected target. The bottom level utilizes the Kanade-Lucas-Tomasi (KLT) feature point tracker which identifies the local point correspondence across image frames. The particle filter at top level, which maintains the relation between target and feature points, estimates the tracked target state. The overall performance has been validated in the experiments.

Keywords:

Visual tracking, Moving camera, Optical flow.

1. Introduction:

Visual surveillance in dynamic environment has drawn much attention nowadays. It has a wide spectrum of researches, including access control, human or vehicle detection and identification, multi-target visual tracking, detection of anomalous behaviors, crowd

Statistics or congestion analysis, etc. In order to construct a wide-area surveillance system economically, we utilize the limited field of view of one single camera to track multiple targets with might and main. This is the key concept and contribution in this paper. Detection and tracking of multiple targets at the same time is an important issue in a wide variety of fields recently. Our goal is to develop a hybrid multi-target detection and tracking system with real-time performance. In a general surveillance system with a single pan-tilt camera, the camera is typically installed at a fixed location. The camera can expand its field of view by commanding its pan and tilt motors. The target is tracked in the image plane, i.e., the target motion is observed with respect to the moving camera platform coordinate.

In order to control the pan-tilt camera to dynamically track the moving objects, we construct a well defined spherical coordinate frame centered at the camera platform. The original image coordinate is then transformed into the spherical camera platform coordinate. Furthermore, the images, target states, and camera actions in this paper are all defined on the spherical camera platform coordinate system. Since we desire to track targets and keep on detecting new ones on a moving camera platform at the same time, the traditional motion detector based on the background subtraction cannot be applied here. Other detecting techniques utilize the predefined target's image information, such as a specified color histogram, an template model of texture, can still work in the moving camera scenario.

However, they are sensitive to the lighting variation. Some other learning based detect or like the AdaBoost face detector [8] may not be influenced by the lighting. When considering the detection and tracking objects at the same time, the learning based detectors are not fast enough such that the real-time performance cannot be fulfilled. For the target tracking or high-dimensional estimate, the comprehensively search in the state space is computational expensive, thus making the system incapable of being real-time. The Monte Carlo method is one solution to this obstacle. By approximating the probability density function in state space with discrete samples, we can obtain the estimate from the sample set. Particle filter or sequential Monte Carlo (SMC), which is based on the Bayesian filtering framework, has been presented to estimate non-Gaussian and non-linear dynamic processes [17].

The sampling importance sampling (SIS) particle filter is also applied to visual tracking and cooperates with auxiliary information knowledge, which is well-known as ICONDENSATIO Nalgorithm [4]. Markov chain Monte Carlo (MCMC) [2] has been proven to perform excellently for drawing the particles. Single [3, 4] or multiple [2, 18] particle filter shave their nature to efficiently represent multi-model distributions. There are a lot of researches about the target tracking on a moving camera and the camera action decision [6,7]. The optical flow of local point in image sequence can be robustly evaluated by the Kanade-Lucas-Tomasi (KLT) feature tracker [1, 12].

Some researchers also employs the KLT tracker to improve the tracking performance [10]. However, the feature point tracker can only provide the point correspondence across frames which do not involve the concept of a target region or target state estimation. The rest of this paper is organized as follows. Section 2 first introduces the input/output hidden Markov model (HMM) and the spherical camera platform coordinate for tracking target on a pan-tilt camera. The particle filter for tracking target at top level together with the KLT feature tracker

at bottom level is described in section 3. Section 4 demonstrates the experimental results and efficiency of our system. The conclusion and future work are given in section 5.

2. METHODOLOGY:

In this work significant modifications have been proposed to help radiologists in performing better and more accurate diagnosis of left ventricular myocardium. The implementation of image processing techniques had been explored, together with the analysis and validation of proposed ideas. The proposed methodology for segmentation is:

- 1) Develop a system for automatically extracting the myocardium from cardiac CT images without using training images.
- 2) A coarse-to-fine strategy, consisting of global localization and local deformations, is applied the myocardium segmentation. Shape segmentation provides seed regions for region rowing while the latter reconstructs a heart surface for the shape segmentation.
- 3) The system is mainly be divided in two major phases as localization of left ventricle and myocardial wall segmentation.
- 4) An automatic method is provided for localization of left ventricle. Previous methods uses low level information from voxels but proposed method captures global geometric characteristics of ventricle. Hence, it is not sensitive to such issues as variability in ventricle shapes and volume coverage's.
- 5) After segmentation active contour model is involved to initialize automatically and robustly. Also, training image is not required in proposed method, which is necessary in the cases where the number of images available is limited.

This method is influenced by the opinions of clinical collaborators.

This system for extracting the myocardium from cardiac CT images will reduce manual measurement, improve consistency, reduce human intervention and operator dependency, avoid competency factor and human errors, while it will also produce reliably meaningful images and measurement, so as to support future studies in a clinical setting.

3. PROPOSED SYSTEM DESIGN:

3.1 Input Image:

Input to the system is 8-bit gray scale CT scan image in JPEG format. As JPEG images give better preprocessing results.

3.2 Preprocessing:

Medical images have unevenly distributed gray values. So, there is need of histogram equalization. Contrast-limited adaptive histogram equalization operates on small regions in the image, called tiles, instead of on the entire image for better local enhancement. Contrast of each tile is enhanced, thus histogram of the output region approximately matches the bell shape histogram.

3.3 Filtering:

In preprocessing filtering is used with Gaussian filter for noise removal as CT scan images are corrupted by noise which is random and spread over all frequencies. It is implemented using weighted sum of pixels in successive windows. The weights give higher significance to pixels near the edge i.e. they reduce edge blurring. Weights are computed according to a Gaussian function as

$$g(i, j) = c \cdot e^{-\frac{i^2 + j^2}{2\sigma^2}}$$

Where, σ is user defined. The optimal performance is obtained for $\sigma=0.006$ and $c=0.5$.

3.4 Thresholding:

From a grayscale image, need to separate out the regions of the image corresponding to objects in which

we are interested, using thresholding with automatic threshold generation using otsu's method. The input to thresholding operation is typically a grayscale or color image. In the simplest implementation the output is a binary image representing the segmentation. Black pixels correspond to background and white pixels correspond to foreground.

3.5 Feature Extraction:

The Canny edge detector is used for edge detection. The result of applying an edge detector to an image gives a set of connected curves that indicate the objects boundaries, the boundaries of surface mark images well as curves that correspond to discontinuities in surface orientation. This significantly reduces the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, and by preserving more important structural properties of an image.

3.6 Localize Left Ventricle:

The geometric features of the heart are used for localization. Assumption is that the orientation of a CT image is given and there is sufficient contrast between blood pool and myocardium. For localization of the LV a deep concave boundary on the blood pool surface is found as discussed in 3.7 and 3.8.

3.7 Extract Blood Pool Surface:

Since CT images have standardized gray levels, thresholding of it is done to highlight the blood pool region. After that, a morphological opening operator is used to remove noisy arteries and cut spines that may be residing in the same connected component of the heart. The largest attached component is chosen and triangulated as the blood pool surface

3.8 Detect Apex Point:

The apex point is one salient feature which is used to locate the left ventricle. Its location is determined by estimating orientation of ventricles and by searching the left ventricle apex, which is the left tip

point with respect to the estimated orientation. To estimate the orientation of ventricles, the convex hull of the blood pool surface is first constructed. Possible apexpoint locations are given by,

$$V_{ch}(\tilde{P}) = \{ \tilde{P} | K(\tilde{P}) > \mu_K + \sigma_K \cap y(\tilde{P}) > t_y \} \quad 2$$

Where $K(\tilde{p})$ = Gaussian curvature at each vertex \tilde{p} of the convex hull, μ_K = mean and standard deviation of $K(\tilde{p})$, t_y = threshold i.e. it defines the region of interest for the ventricle.

3.9 ROI:

To find region of interest of left ventricle region, region growing method is used because it is less sensitive to position of initial contour, it performs well in the presence of noise and with weak edges or without edges. It has a global segmentation property and can detect the interior and exterior boundaries at the same time, regardless of the position of the initial contour in the image. ROI is found out by applying energy functional as

$$E_{RS}(\phi) = \int_{\Omega} -p(f(x))H(\phi(x))dx + \lambda_{RS} \int_{\Omega} \delta(x) |\nabla \phi(x)| dx \quad (3)$$

In above equation first term measures intensity homogeneity inside the contour and second term controls the smoothness. Degree of smoothness is controlled by “sussman” method.

3.10 Active Contour Model (ACM):

The ROI obtained in previous step is refined using ACM which lead to energy minimization for more accurate result. The number of iterations is selected manually and its value is 250 for optimal performance. The ACM algorithm is [3]:

1. Find initial cut contour C_0 .
2. Next step is to refine initial cut contour C_0 .
3. Initialize the level set function U with C_0
4. Construct a narrow band $\Omega_{M_{bp}}$ around the current contour on M_{bp}
5. Update U in $\Omega_{M_{bp}}$, according to

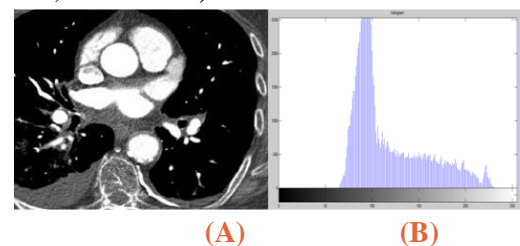
$$\left(|\nabla_{M_{bp}} U| \nabla_{M_{bp}} \cdot \left(\frac{\nabla_{M_{bp}} U}{|\nabla_{M_{bp}} U|} \right) \right)$$
6. $U(p,t+1) = U(p,t) + dt$ Where dt is the time step in discretizing U
7. Find the new zero level set of U to update the contour C .
8. Repeat steps 2-4 until it converges or reaches the maximum number of iterations.

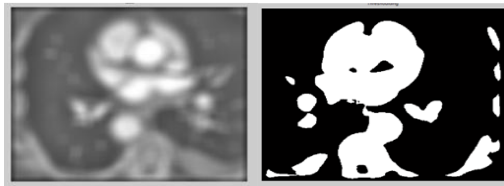
3.11 Diseased Area Fraction:

The Area fraction is given in percentage area with respect to segmented heart portion. From area of fraction, the stage of disease can be assigned by defining standard rules in consultation with radiologists. Stages assigned are normal, moderate and critical.

4. EXPERIMENTAL RESULTS:

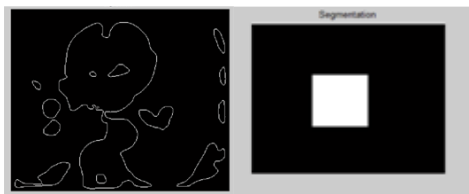
Proposed system starts with preprocessing on input CT scan image. The steps of preprocessing include histogram equalization, Gaussian filter for noise removal purpose, and thresholding for binarization of image canny edge detection for better extraction of different boundaries. This preprocessing step enhances the image for further processing. Accuracy is obtained with proposed system by initialization of ROI, iterating ROI and getting area of interest. Finally system calculate diseased area fraction and based on that stage of disease is mentioned (i.e. normal, moderate, and critical).





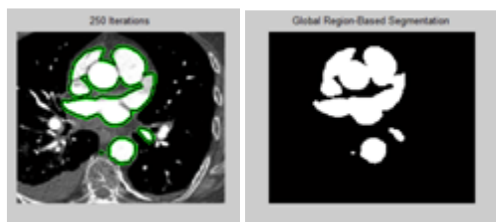
(C)

(D)



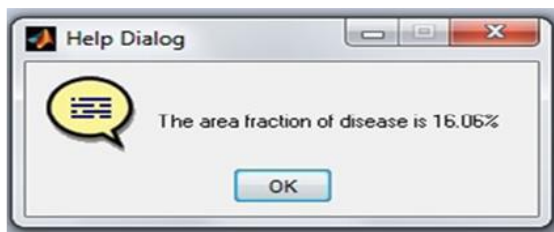
(E)

(F)



(G)

(H)



(I)



(J)

Figure 1

(A) Original Image (B) Histogram

(C) Filtration (D) Thresholding Image

(E) Edge Detection Discussion (F) ROI

(G) Iterations (H) Global Region Based

Segmentation (I) Help Dialogue1 (J) Help Dialogue1

4.1 Test Result of patients:

Table below shows test results of different patients. It includes area fraction, total analysis time and state of detected disease which are verified with the results of radiologist.

Table 1 with different datasets the results of the system in terms of area fraction, analysis time and stage detected

Date Set	Area Fraction (%)	Total Time For Analysis	Result
1	16.06	9.0493	Moderate
2	12.62	6.0479	Moderate
3	25.3	7.7651	critical
4	11.92	3.9026	Moderate
5	11.31	3.4298	Moderate

5. CONCLUSION:

Diagnosis of CVD's mainly depends on different cardiac imaging models which dominantly focused on extraction of myocardium wall considering large shape variability within cardiac cycles and weak edges between epicardium and tissues. The extraction is carried out with various segmentation methods as discussed with every method with some limitations such as less accuracy, more analysis time required, large no of training set is required.

To obtain further accurate and robust segmentation, we have proposed global region growing method in iterative way, which is less sensitive to the position of the initial contour, it performs well in the presence of noise and with weak edges or without edges for CT images. It has a global segmentation property and can detect the interior and exterior boundaries at the same time, regardless of the position of the initial contour in the image.

The proposed system implemented in two stages to eliminate limitations of existing methods. To obtain accurate results proposed algorithm is applied iteratively to refine the solution. Proposed method requires less time (9.0493 Sec for given input image) as compared to existing method i.e. manual method (20 min for the same image). Existing method do not provide diagnosis of disease.

Proposed method first calculates area fraction of disease and then gives stage of disease in terms of normal or moderate or critical. With area of fraction less than 10% the stage is normal, with area of fraction greater than 10% but less than 50% the stage is moderate and above 50% the stages critical. Also existing method suffers from inter and intra observer variability, which is avoided by the system. Proposed method is validated using available data set and commented by the radiologist for better performance verification.

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