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IMAGE AND VIDEO PROCESSING TASKS IN COMPUTER AIDED MEDICAL INTERVENTIONS ON THE EXAMPLE OF TRANSBRONCHIAL BIOPSY

The paper presents signal processing tasks dedicated to image based computer navigation system for positioning of bronchoscope tip during transbronchial needle-aspiration biopsy. The paper has the tutorial form with extensive bibliographical review and examples based on authors' original work. The reconstruction, segmentation and visualization of computed-tomography (CT) are discussed. The navigation exploits principle of on-line registration of real images coming from endoscope camera and virtual ones generated on the base of CT data of the patient. When these images are similar the assumption is made that the bronchoscope and virtual camera have approximately the same position and view direction. In the paper the following design aspects are described: reconstruction of bronchial tree from CT data, correction of bronchoscope camera non-linearities, fast, approximate estimation of endoscope egomotion, and finally 2D, 3D registration of real and virtual images.

1. INTRODUCTION

Virtual bronchoscopy [1] CT-guided approach represents a modern solution to the difficult problem of bronchoscope tip positioning during medical procedure of transbronchial needle-aspiration biopsy. It makes use of on-line registration of *real* 2D images (coming from the bronchoscope) and *virtual* ones (obtained from virtual camera looking inside the model of bronchial tree, reconstructed from the CT patient data

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by means of segmentation). Usually, the registration of these two-source images is performed using in-the-loop maximization of their: correlation [2] or mutual information [3]. To speed-up search for virtual camera position, egomotion of the bronchoscope camera can be estimated from video stream using corresponding points and epipolar geometry [2], or optical flow methods and perspective geometry [4]. In turn, next position of the endoscope camera can be predicted and tracked with Kalman [5] or Monte Carlo [6] particle filters. Using *shape-from-shading* technique it is also possible to extract 3D model of the airways tract from the endoscopic video and try to register it to the 3D model deduced from the CT scans. First such attempt has been reported in [7] and further elaborated in [8].



Fig.1 Block diagram of the system under development

The architecture of the bronchoscope navigation system that we are currently developing is presented in fig.1. In the paper image and video processing tasks concerning this system are presented. The paper has the form of tutorial. The following aspects are addressed in the next sections: data reconstruction form CT, segmentation of anatomic structures, visualization of bronchial tree, correction of camera non-linearities, fast, approximate estimation of endoscope egomotion and 2D, 3D registration of real and virtual images.

2. COMPUTED TOMOGRAPHY

The theoretical background of Computed Tomography (CT) has long history with the beginning in 1895 when W. Röntgen invented *x*-rays. The mathematical principles of CT were first investigated by J.Radon in 1917 and then extended by Kirillov in 1961. A clinical CT scanner was first presented in 1972 and its inventors Cormack and Hounsfield were awarded the Nobel Prize in medicine in 1979. Nowadays medical

imaging of CT is the important, noninvasive tool used for diagnostic and surgical planning. Tomography literally means 'slice' or cross-sectional imaging. The idea is to reconstruct the image from projection data obtained by integration along different directions. The detailed analysis of computed tomography is given in [9-12]. Here we only present the main concept of data reconstruction. Fig.2a depicts *parallel-beam* projection; the projections are taken at different angles Θ . The line integral $P_{\Theta}(t)$ represents the total attenuation of x-ray t by the object f(x, y):



 $P_{\Theta}(t) = \int_{(\Theta,t) \text{line}} f(x, y) ds$ (

(1)

Fig.2 a) Parallel beam projection b) Fourier Slice Theorem illustration

using a delta function and $x\cos\Theta + y\sin\Theta = t$, this can be rewritten as

$$P_{\Theta}(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos \Theta + y \sin \Theta - t) dx dy$$
(2)

The function $P_{\Theta}(t)$ is known as the *Radon transform* of the function f(x, y). The aim of computed tomography is to reconstruct the image f(x, y) from projection data $P_{\Theta}(t)$ obtained along different angles Θ . The inverse Radon transform can be computed with the help of *Fourier Slice Theorem*, which says that [9]: the Fourier transform of a parallel projection of an image f(x, y) taken at angle Θ gives a slice of the two-dimensional transform, F(u, v), subtending an angle Θ with the u-axis. In other words, the Fourier transform of $P_{\Theta}(t)$ gives the values of F(u, v) along line BB in fig.2b. This can be written as:

$$S_{\Theta}(w) = F(w, \Theta) = F(w \cos \Theta, w \sin \Theta)$$
(3)

where:

$$S_{\Theta}(w) = \int_{-\infty}^{\infty} P_{\Theta}(t) e^{-j2\pi w t} dt , \ S_{\Theta}(w) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{j2\pi w (x\cos\Theta + y\sin\Theta)} dx dy$$
(4)

According to the above theorem F(u, v) (Fourier transform of f(x, y)) can be reconstructed from infinite number of projections. Knowing F(u, v), the object function f(x, y) can be recovered by using the inverse Fourier transform. The problem arises that in practice we only have finite number of projections, what results in sampling frequency plane along radial lines as shown in fig.3a. Computing inverse Fourier transform of F(u, v) would require interpolation of values on rectangular grid. The algorithm that is currently being used in almost all applications of straight ray tomography is called *filtered backprojection*. Looking at fig.3b one can intuitively say that instead of slice of the cake he gets only very thin line of one projection. To get the same mass of the cake this thin line (each projection) should be weighted (or multiplied) by the function with the values increasing with frequency. For K projections over 180° at a given frequency w, weighting factor equals $2\pi |w|/K$. The shape of the weighting filter in frequency domain is shown in fig.3c.



Fig.3 a) Sampling of frequency plane by projections, b) ideal sampling of frequency plane, c) the frequency shape of weighting filter

Analytical expression for object function f(x, y) can be derived as:

$$f(x,y) = \int_{0}^{\pi} \left[\int_{-\infty}^{\infty} F(w,\Theta) |w| e^{j2\pi wt} dw \right] d\Theta$$
(5)

The inner integral represents filtering, where the frequency response of the filter is given by |w|. After filtration the signal is backprojected, i.e. value of each filtered pro-

jection is added to all points in f(x,y) that lay on the way of the ray. The computer implementation issues are detailed in [9].

For testing quality of tomography reconstruction the phantom of the head was designed by *Shepp and Logan*. The phantom shown in fig.4a is built from 10 ellipses. Fig.3b,c shows reconstruction for different number of projections. For small number of projections star-like distortions are visible in the reconstructed image.



Fig.4 a) Head phantom of Shepp and Logan, size of the picture is 256x256 pixels, b) reconstruction from 367 rays and 10 projections, c) reconstruction from 367 rays and 91 projections

Medical CT scanners, because of easier hardware realization, use *fan-beam* projection. Fig.5a depicts *third-generation* CT scanner with the *x*-ray source and detector array rotated around the object. Fig.5b shows *fourth-generation* CT scanner, where patient lying on the bed is moved thru rotating *x*-ray source and detector array. Fourth-generation CT scanner complicates the image reconstruction and suffers from slightly blurred images but enables to scan large regions of the patient in a single breath hold.



Fig.5 a) Third - generation x-ray CT scanner with fan beam projection b) Fourth - generation helical (spiral) CT scanner

Medical CT operates under a number of constraints, including the amount of radiation dose per scan. The dose requirement for medical CT leads to limitations on imaging performance and spatial resolution. Obtaining better image quality on hard tissue or bone scans requires higher source energy. Alternatively, obtaining greater spatial resolution requires more collimation, smaller detectors, or, for some scan geometries, more data acquisition. All of these circumstances result in more *x*-ray dose delivered to the patient or greater discomfort to the patient (has to sit still longer). It is also difficult to keep the patient or organs from moving, while the most disturbing are respiratory and heart-beat movements. Some methods of reducing motion artifacts are described in [10] including established methods, fast-acquisition methods, respiratory gating, electrocardiographic (ECG) gating and signal processing methods.

Usually reconstruction algorithm is integrated with CT scanner and output data are already reconstructed and has form of gray scale images. Results presented in this paper were obtained from CT data generated by Siemens Somaton 10 with voxel size of 0.6x0.6x1 [mm] (for X, Y, Z axes respectively). Typical examination results in about 300 images with size 512x512 and 12-bit resolution.

3. SEGMENTATION

Image segmentation is the operation of grouping image pixels into separate objects present in the picture. The first step of segmentation algorithm is most often feature extraction and then checking if the specific pixel belongs to the object of interest. In medical CT, data segmentation is used to isolate biological structures of interest like whole organs, e.g. bronchial tree in fig.6, or some interesting, smaller structures like lymphatic nodes in fig.7 or tumors. Generally segmentation algorithms can be divided into four major groups: *pixel-based*, *region-based*, *edge-based* and *model-based methods*.

Pixel-based methods operate on one pixel at time and thus are the simplest but also most sensitive for noise. They usually require intensive preprocessing (e.g. feature extraction, filtering, illumination correction etc.). The gray valued picture is compared with the threshold and converted to the binary image with 0 for values lower then threshold. *Thresholding* is usually fast enough to operate in real time allowing for interactive setting of the threshold. Thresholding with a set of thresholds with different values (ranges) is called *slicing*. For color images thresholds can be applied for each different RGB plane or in other color spaces [19]. Appropriate threshold value is chosen on the base of image intensity histogram. If the histogram is bimodal (or multimodal), a common strategy is to search for minima. For improved determination of minima in histogram following algorithms can be used: removing edges (intermediate values) from image, assuming known (e.g. gaussian) distribution for each mode, filtering (lowpass, median etc.). Several analytic approaches to the setting of a lumi-

nance threshold have been proposed [20-23]. If the background of an image is nonuniform, it is often necessary to adapt the luminance threshold to the mean luminance level. This can be accomplished by subdividing the image into small blocks and determining the best threshold level for each block. Clustering algorithms for image segmentation have been also developed [24, 25]. Unfortunately histograms contain no information on position, which is of prime importance in segmentation. Pixel-based methods are sensitive against uneven illumination.

Region-based methods search for similarities or consistency in the image. Lowpass filtering is an example of sliding neighborhood operation that enhances consistent characteristics of a region. Morphological operations are also used in image enhancement stage before segmentation. The pixel is classified as belonging to the object with checking *connectivity* with its neighbors and not only gray scale luminance value. Distinguishing textures with similar intensity can be done by several neighborhoodbased operations [14]: the small segment Fourier transform, local variance (or standard deviation), the Laplacian operator, the range operator (the difference between maximum and minimum pixel values in the neighborhood), the Hurst operator (maximum difference as a function of pixel separation), and the Haralick operator (a measure of distance moment). The popular region-based methods are: region-growing, spitand-merge and watersheds. Region-growing is one of the conceptually simplest approaches to image segmentation. Neighboring pixels of similar amplitude are grouped together to form a segmented region. In practice additional constraints must be placed on the growth pattern to achieve acceptable results [26]. Split-and-merge image segmentation techniques [27] are based on a quad tree data representation whereby a square image segment is broken (split) into four quadrants if the original image segment is nonuniform [28, 29] in attribute. If four neighboring squares are found to be uniform, they are replaced (merge) by a single square composed of the four adjacent squares. Watershed exploits topographic and hydrology concepts in the development of region segmentation methods [30-33, 60].

Edge-based methods search for differences in the image. They are based on the fact that the position of the edge is determined by an extreme of first-order derivative or zero crossing in the second-order derivative. Region reconstruction from edges requires grouping edges into chains that correspond to the sides of the region. False edges and missed edges are two most common problems associated with this approach. Edge detection can be done with following special filters: *Sobel, Prewitt, Log, Laplacian, Canny*. Next *edge relaxation* or *graph searching* method is used for forming chains from detected edges. Edge-based methods are robust against uneven illumination. Edge-based segmentation methods are sequential and cannot be performed in parallel on all pixels simultaneously. Typically image is scanned line by line for maxima of the gradient magnitude then *tracing algorithm* follows the maximum of the gradient around the object until it reaches starting point. It is also taken into account that an object is characterized by adjacent pixels. If an image is noisy or if its region attributes differ by only a small amount between regions, a detected boundary may

often be broken. The following edge linking techniques can be employed to bridge short gaps in such a region boundary: *Curve-Fitting Edge Linking* [34-36], *Heuristic Edge-Linking Methods* [37-39], *Hough-Transform Edge Linking* [40]. *Snakes Boundary Detection* [41, 42] is a method of molding a closed contour to the boundary of an object in an image. The snake model is a controlled continuity closed contour that deforms under the influence of internal forces, image forces, and external constraint forces to fit the edge of the object.

Model-based methods assume that the shape of the object is known. The simplest case is straight lines segmenting in the image with the use of *Hough transform*. Segmentation of partially corrupted objects is possible with those methods thanks to the knowledge of the shape. High computational cost is the main drawback of Hough transform methods.

Especially in medicine there are no general algorithms to solve all kinds of segmentation problems. For each kind of problem a single solution has to be developed or existing methods must be adopted. Very often segmentation techniques are so called *hybrid methods* that use several methods from different classes. Robust, automatic segmentation of bronchial airway tree is difficult for many reasons: anatomy-related (e.g. airway obstructions, heart beat artifacts), image reconstruction artifacts, partial volume effect, image noise, necessity of low-dose scans. Lately developed algorithms for segmentation of airway tree mainly include region-growing based methods [43-46], morphology-based methods [47-49], and combinations of the two [50, 51]. Other methods include *rule-based* methods [52, 53], *energy function minimization* [49], and *region of interest* (ROI) modification-based techniques [54]. In [55] a *front-propagation* algorithm for airway tree segmentation is used. Another group of segmentation methods is based on *fuzzy connectivity* [56-58].

In our work [59] airway tree was segmented with the following steps: data smoothing with 3D gaussian filter, global thresholding and checking 26-connectivity. Segmentation results are depicted in fig.6a. Fig.6b shows example of segmentation explosion caused by improper threshold selection. From fig.6b it is seen that bronchial tree is not homogeneous and thus applying local (adaptive) thresholds can be fruitful. The depth of segmentation presented in fig.6a is sufficient for task of navigation as bronchofiberscope cannot penetrate smaller tree branches because of its size.

We also segmented other anatomical structures like lymphatic nodes [60] with the concept of transparent visualization of those during biopsy. We proposed modified 3D marker-based watershed segmentation algorithm supported by morphological filtering, edge detection and histogram equalization. This method reduces problems with oversegmentation, which are common in classic watershed algorithm [32]. The principle of the proposed method can be illustrated by water immersing from the bottom (object and background markers) to maximum magnitude of the gradient image value. When two neighboring catchment basins (water comes from different marker) meet, a dam is created to separate basin from the other. Finally, catchment basins are a result of the segmentation process. Object markers become regional maxima after perform-

ing morphological filtering called *opening by reconstruction* and *closing by reconstruction* on the data. Then we clean the edges of the foreground markers using *closing* followed by *erosion*. Binary background is computed by optimal thresholding [23]. Next, the background mask is subjected to *skeletonization by influence zones* (SKIZ). Background markers are result from the SKIZ. The proposed technique allows visualization of chosen anatomic structures as shown in fig.7.



Fig.6 Results of airway tree segmentation for: a) threshold 200, b) threshold 320



Fig.7 Segmented bronchial tree; I – bronchial tree, II – lymphatic nodes, III – Arteria pulmonaris sinstra, IV – Vena cava superior

4. VISUALIZATION OF BRONCHIAL TREE

Three-dimensional (3D) visualization is widely used in modern medicine, mainly due to the rapid growth of computing power. Thanks to the fast evolution of consumer graphics accelerators driven by entertainment markets interactive medical data visualization is no longer restricted to expensive workstations and dedicated hardware. The 3D computer-based visualization of bronchial tree is used as accessory noninvasive method of pulmonary diagnostics, as a tool supporting the real bronchofiberoscopic procedures or for training purposes. The basic form of inspecting CT relies on examination of two-dimensional images showing consecutive cross-section of the body and requires considerable experience and spatial imagination from physicians. 3D visualization of bronchial tree significantly enhances inspection of CT data, with options such as viewing from arbitrary camera positions, transparent views of interesting anatomical structures, imposed images from other examinations and others. Relatively limited use of 3D visualization in the past was caused by limited available technical resources. Data obtained during CT examination of the chest yielding 360 scans of resolution 512x512 pixel will take about 200 MB of memory space. Processing of such volume of data in real time would require not only very high bandwidth of CPU and memory bus but also extremely fast CPU and graphics accelerator. PC systems available now are sufficient to deal with such volumes of data. The main 3D visualization techniques can by broken into two categories: surface rendering and volume rendering. Both can by supported by hardware-base graphics accelerator.

Surface rendering is an *indirect* method of obtaining an image from a volume dataset. This method includes two stages: generation of 3D surface from 3D data and proper visualization process relying on the image generation by graphics accelerator on the basis of prepared surfaces. There are a number of techniques for implementing surface rendering like the Cuberilles algorithm [61], which produces clouds of objects (e.g. cubes), Marching Cubes [62] or Marching Tetrahedra [63], which generates triangle mesh. The main disadvantage of this approach is the computationally expensive preprocessing. Furthermore, for high resolution data sets the number of generated graphical primitives (triangles, points) can be extremely high. To reduce the number of triangles the mesh may be decimated [64-66], or the set of primitives can be reduced in the mesh generation process, via a feature-sensitive octree method [67] or discretized Marching Cubes [68]. Screen-adaptive surface rendering algorithms that take advantage from the fact that during viewing many of the primitives may map to a single pixel was also developed: Dividing Cubes [69], Trimmed Voxel Lists method [70].

Volume rendering or direct volume rendering is the process of creating a 2D image directly from 3D volumetric data, without creation of intermediate surfaces consisting of triangles [71-73]. Volume rendering [71] can be achieved using an object-order, an image-order, or a domain-based technique. Hybrid techniques have also been proposed. The high computational complexity of volume rendering has led to a great va-

riety of approaches for its acceleration such as: early ray termination [71], post-rendering warps for magnified viewing [74], the splatting of pre-integrated voxel basis functions [75]. The latter two gave rise to independent algorithms, that is, shear-warp [74] and splatting [75]. Acceleration techniques generally seek to take advantage of properties of the data, such as empty space, occluded space, and entropy, as well as properties of the human perceptional system, such as its insensitivity to noise over structural artifacts [76].

Currently available graphics cards are characterized by immense ability of 3D data processing. They are developed and optimized for processing triangle meshes, which are used for surface rendering. Volume rendering algorithms usually require much more memory than currently available hardware offers. Both techniques can use fully programmable graphic pipeline.

The visualization part of the navigation system was developed with Borland C++ Builder and Visualization ToolKit (VTK) cross-platform - an open-source library [77]. The Visualization ToolKit uses OpenGL API for 3D graphic card. We use surface rendering technique for the sake of good performance and quality of generated virtual bronchoscopy images. Surface rendering includes two stages: generation of three-dimensional surface representing bronchial tree walls from CT data and visualization process via graphics card. The first stage to generate the 3D surface is loading the DICOM file with patient's CT data. The gray scale images from CT are depicted in fig.8a. In the next step the CT data are cut back to reduce their size. Then isosurface at the level -500HU is generated using marching cubes algorithm [62]. The isosurface on this level goes through the data that represent walls of bronchial tree. The result of computations is the continuous triangular mesh, as shown in fig.8b, that describes surface of patient's bronchial tree. To improve rendering performance triangle strips are also created. For that data a mapper generates OpenGL rendering primitives and actor object controls mesh properties. After this data processing virtual bronchoscopy image is generated as shown in fig.8c. The generated surface can be saved to file for later fast use.



Fig.8 CT visualization: a) DICOM CT gray scale images, b) triangular mesh, c) rendered bronchoscopy image

To improve the quality of virtual bronchoscopy images and achieve maximum resemblance with real bronchoscope camera illumination conditions, the virtual light source was set up. This light source moves along with the camera and the position of light source is the same as camera position. The light is configured as positional (headlight), and the cone angle corresponds to camera cone angle. To prevent overexposing of nearest surfaces the irregular light intensity along the cone angle was used. Light fading attenuation was used for distance simulation.

5. ALGORITHMIC CORRECTION OF CAMERA GEOMETRIC DISTORTIONS

Wide-angle bronchoscope camera is biased by nonlinear geometric (barrel) lenses distortion. The correction of those distortions is of primal importance in case when picture from bronchoscope camera is used for further analysis like motion estimation or image registration. In general, correction methods for barrel distortion rely on computing the distortion center and considering both radial and tangential components [78, 79]. In our system video bronchoscope Olympus BF-160 was used and we found out that tangential components can be neglected [80], what is a common simplification [81, 82]. The methodology based on the concepts presented in [81, 82] was used for correction of bronchoscope camera distortions. As a test image we chose black dotes placed on straight lines. The distorted image obtained from bronchoscope camera is presented in fig.9a. The applied correction algorithm was based on mean-square optimization of the criterion that describes the degree of straightness of each line in the picture (the sum of distances of the points in the line to the best fitted line). Using the model of radial distortions, the following coefficients of the polynomial relating the radius in distorted image r_c to the radius in undistorted image r were found (in pixels):

$$r_{c}(r) = 4.2009 \cdot 10^{-8} r^{4} + 1.5991 \cdot 10^{-10} r^{3} + 3.7892 \cdot 10^{-13} r^{2} + r$$
(6)



Fig.9 a) Test image taken with the bronchoscope camera, b) Corrected image

Unlike [81, 82], the center of distortions was calculated upon conducting many optimizations in the neighborhood of geometric center of the image, what led to better correction results. The image after correction procedure is shown in fig.9b. In fig.9b the perspective shortage is seen that was caused by non-perpendicular position of the bronchoscope camera to the test image. The slight lack of perpendicular placement of test image dose not affect correction algorithm, as horizontal and vertical lines still have to remain straight.

6. AUTOMATIC GENERATION OF NAVIGATION PATH IN VIRTUAL BRONCHIAL TREE

Unlike the case of real camera, the movements of virtual camera are not constrained by bronchial wall. The virtual camera is moved along indices of 3D matrix with CT data. For keeping virtual camera inside the bronchial tree *navigation path* should be computed. Once having the path, the physician can operate on intuitive directions like: forward, backward, left, right etc. independent of current camera position in 3D CT matrix. Thus navigation path is used for virtual bronchoscopy, planning transbronchial biopsy and guiding bronchoscope's tip during biopsy. Algorithms for automatic generation of navigation path in bronchial tree are based on one of the following methods [83, 84]: *branch following* [85-89], *skeleton-based techniques* [90-94], *thinning algorithms* [95-98], *front analysis* [55,99-103], *distance transform* [104-109].



Fig.10 a), b) Successive steps of computing navigation path in bronchial tree (at the bottom the values of distance transform on the sides of the cube are shown); c) Path computed after first iteration (points connected by the line), starting points for next iterations (points not connected)

In [59] we proposed new algorithm based on the distance transform, acting on the segmented bronchial tree, and original iterative method for path searching. The proce-

dure is equipped with additional set of rules that prevent detecting false paths. The algorithm for path detection starts with placing the cube at the beginning of the bronchial tree, and then the cube is moved according to values of coefficients of distance transform on its walls. Figs.10a, 10b show the position of the cube in bronchial tree during successive steps and values of distance transform on its sides. The transform values on the sides of the cube are used for setting up the next point of the path. Fig.10a depicts the beginning of the path, in this case distance transform shows that next point of the path should be either in Z or -Z direction. As the direction -Z means going back to previously computed point, the direction Z is chosen. In the case depicted in Fig.10b, from possible -Z, Y and -Y, the direction Y is used, while the direction -Y is stored and becomes starting point for next iteration (possible branching node) and direction -Z is neglected for the same reason as previously. In fig.10c points connected with lines are depicted, which form the path computed after first iteration. Consecutive iterations start at points stored as possible branching nodes (points not connected in fig.10c). The algorithm ends up after checking all branching nodes (what takes 49 iterations in the presented example). Finally, a polynomial of 6-th degree is fit to points of the path to achieve smooth trajectory of virtual camera inside bronchial tree.

7. FAST ESTIMATION OF BRONCHOSCOPE EGOMOTION

Egomotion is a term known from mobile robot applications. In our problem it is an attempt to track motion of bronchoscope tip relative to bronchial tree. The commonly adopted approach to egomotion estimation relies on a set of a few velocity vectors for features in rigid environment [110]. Such features are often corners for in-room or instreet environment. This approach is generally susceptible to noise in velocity vectors and generates ill-conditioned equations. The human airways form hard conditions to image processing algorithms. Non-rigidity of lung, lack of stable light source and limited set of cross-individual repetitive features (like carina) make the task of bronchial egomotion estimation significantly more difficult. We start our tutorial description of egomotion estimation with geometric relations of 3D motion and apparent 2D motion, then describe methods of egomotion estimation from apparent motion, and finally switch to the method developed for estimation of camera motion in bronchial tree environment.

Let P(X, Y, Z) denotes point in 3D space. By small rotations of Cartesian coordinate system with angles $\alpha(\alpha_X, \alpha_Y, \alpha_Z)$ along its axes and translations with vectors T(t_X , t_Y , t_Z) point P is approximately (sin(x) $\approx x$, cos(x) ≈ 1) mapped into P' according to equation [111]:

$$\mathbf{P}' = \mathbf{R}\mathbf{P} + \mathbf{T}, \quad \mathbf{R} = \begin{bmatrix} 1 & -\alpha_Z & \alpha_Y \\ \alpha_Z & 1 & -\alpha_X \\ -\alpha_Y & \alpha_X & 1 \end{bmatrix}, \quad \mathbf{T} = \begin{bmatrix} t_X \\ t_Y \\ t_Z \end{bmatrix}$$
(7)

The camera image p(x, y) of the point P(X, Y, Z) is the projection of the P(X, Y, Z) on the plane Π towards the center of coordinate system (fig.11). From triangle proportions:

$$x = \frac{fX}{Z}, \quad y = \frac{fY}{Z} \tag{8}$$

where f stands for the camera focal length. Thus 2D coordinates are equal to 3D coordinates rescaled with focal length and point depth Z(f|Z = const).



Fig.11 Projection of 3D point P(X, Y, Z) onto camera plane Π with focal length f. Point p(x, y) is the image of point P

Homogenous coordinate system is obtained by multiplication of coordinates of 2D and 3D vectors by the constant *const* (e.g. equal f/Z or 1) and by extending those vectors with that constant as additional element. The vectors in homogeneous coordinates will be denoted by lower index h (e.g. p_{1h}). Fig.12 depicts epipolar geometry [112-114]. The point P in 3D space is observed by two cameras simultaneously, or by one camera placed in positions K_1 and K_2 in consecutive time instants. The images p_1 and p_2 are projections of P onto planes Π_1 and Π_2 . The line passing through points K_1 and K_2 intersects planes Π_1 and Π_2 in *epipoles* e_1 i e_2 . The plane passing through the optical centers K_1 and K_2 and the scene point P is called an *epipolar plane*. Intersection of epipolar plane and planes Π_1 and Π_2 determines lines l_1 and l_2 that connect points p_1 with e_1 and p_1 with e_2 .



Fig.12 Epipolar geometry

Points p_{1h} and p_{2h} (in homogeneous local coordinate system, *const* = 1) satisfy the equation:

$$\mathbf{p}_{2h}^T \mathbf{E} \mathbf{p}_{1h} = 0, \tag{9}$$

where E denotes 3x3 essential matrix:

$$\mathbf{E} = \begin{bmatrix} e_1 & e_2 & e_3 \\ e_4 & e_4 & e_5 \\ e_6 & e_7 & e_8 \end{bmatrix} = \begin{bmatrix} 0 & -t_Z & t_Y \\ t_Z & 0 & -t_X \\ -t_Y & t_X & 0 \end{bmatrix} \mathbf{R}$$
(10)

Matrix E depends on translations and rotations of camera when moving from K₁ to K₂, see fig.12. The camera motion is the reason of the motion of projections in 2D space depicted in fig.13 and called *optical flow*. Equation (9) states that vectors p_{1h} and p_{2h} are orthogonal with respect to matrix E (p_{2h} is orthogonal to E· p_{1h} , and p_{1h} to E^{*T*}· p_{2h}). Elements of matrix E are not linearly independent. In order to compute 9 elements of E at least 5 pairs of corresponding projection points in two images are required [111]. For greater number of corresponding pairs least-squares solutions are used that are more robust against errors in computed motion vectors of characteristic points. Motion vectors are computed with sub-pixel precision. Many algorithms for computing elements of matrix E (and fundamental matrix F) and then projection parameters (7) are described in literature [111].

To speed-up egomotion estimation [110] in bronchial environment we use simplified model of geometric relations based on cylindrical shape accompanied by the fixation on carina [115, 116], what reduces motion's degrees of freedom to four (forward/backward move, camera rotation, camera tilt in two directions). That is achieved by continuous tracking of a carina (stationary point) illuminated by sensor light, and by analyzing bronchial wall radial moves relative to fixed point by correlation in polar coordinates.



Fig.13 The effect of camera motion (translations t_X , t_Y , t_Z and small rotations α_X , α_Y , α_Z around X, Y, Z axes) on projection (x_0 , y_0) placement of the point (X_0 , Y_0 , Z_0) on 2D plane

To reverse perspective projection from images during correlations we make use of correspondence between z-axis and r-axis that can be derived from the following trigonometric relation (fig. 14b):

$$\frac{R-r}{z} = \operatorname{tg} \varphi = \frac{R}{z+f} \qquad \Longrightarrow \qquad r = R \left(1 - \frac{z}{z+f}\right). \tag{11}$$

Let us note that *R* serves only as a scaling factor of the view.



Fig.14 Applied models: a) segment of bronchial tree (upper perspective projection and *x-z* cross-section),
b) imaging in cylindrical environment with radius *R*, camera focal length *f*, radial image axis *r* and depth from image plane *z*

In the current research we estimate forward motion, after carina stabilization and camera rotation compensation, as arithmetic mean of directional wall motions. Camera tilt is estimated from geometric mean of these directional motions. We assessed algorithm accuracy by series of test in virtual cylinders, virtual bronchial trees and on real operational video sequences from transbronchial biopsy. The results of experiments show that accuracy of bronchoscope cumulated motion estimation is within 5% of distance in virtual environments. In fig.15a the virtual bronchial tree environment with estimated wall motions is shown. Fig.15b shows estimation of cumulated forward/backward motion together with imposed forward virtual camera motion. Disturbing factors in this experiment were camera rotation, and *x-y* plane camera moves. Fig.16a shows forward/backward bronchoscope trajectory during real biopsy. This trajectory suggest similarity of frames 7 and 65, being distant in time but close in space, because of strong backward move followed by forward move. These frames shown in fig.16b and fig.16c confirm this similarity and as a consequence confirm also satisfactory behavior of our egomotion estimation algorithm.



Fig. 15 Example of camera position estimation along *z*-axis in virtual bronchial-tree phantom: a) virtual environment with estimated radial wall-move vectors, b) estimated forward/backward camera trajectories for imposed motion: 1 - camera motion along the path with target fixed on carina, 2 - camera motion with additional camera tilt and rotation and moving target



Fig.16 Example of camera position estimation along *z*-axis in real bronchial-tree: a) estimation result with two frames that are close in space but distant in time marked with 'o', b), c) frames 7, 65 that should be similar as inferred from fig.16a

8. IMAGE REGISTRATION

8.1. 2D REGISTRATION USING MUTUAL INFORMATION

The information from egomotion estimation algorithm about bronchoscope forward/backward incremental motions can speed-up navigation process, but is not sufficient to fully determine the location of *real* bronchoscope tip in relation to *virtual* bronchial tree what is the goal of navigation system. So, before successful navigation will be possible, two tasks have to be completed. The first task is to place the virtual bronchoscope (the source of virtual images) in a position corresponding to real bronchoscope. This is achieved by adjusting position of virtual bronchoscope in such a way that images generated by it were similar as much as possible to images from real bronchoscope. After setting up the virtual camera starting position, the second task calibration of egomotion estimation algorithm is performed. Having two images from real camera at positions z_0 and z_0+d , where z_0 is the starting position and d is outcome of egomotion estimation algorithm, using appropriate image similarity measure we try to find such a displacement of virtual camera position which makes virtual image as similar to real one as possible. Given d corresponding displacement calibration is done. After this initial steps navigation system works as depicted in fig.1. Outputs from egomotion estimation algorithm are used for coarse virtual camera positioning, then image registration algorithm is used for finer adjusting.

The methods enabling the registration of images from the same or different sources were extensively developed through last decades. Numerous papers were published on this topic [117]. In our approach in both described above tasks mutual information [118, 119] is used as an image similarity measure. It is based on the concept of joint entropy as given by Shannon for determination of communication's channel capacity and is defined as follows

$$I(u,v) = H(u) - H(u | v),$$
(12)

where H(u) denotes the measure of uncertainty about the value of random variable u, and H(u|v) denotes the same measure but determined with the assumption that value of random variable v is known. In this way I(u,v) expresses how much the uncertainty about value of u decreases after getting to know the value v. It is obvious that if the value of conditional entropy H(u|v) decreases, the value of mutual information I(u|v)increases. Using the Bayesian theorem: P(A,B)=P(A|B)P(B) and the definition of Shannon's entropy

$$H(u) = -\sum_{i} p_{u}(i) \log p_{u}(i), \qquad H(u,v) = -\sum_{i,j} p_{uv}(i,j) \log p_{uv}(i,j)$$
(13)

the equation expressing mutual information (MI) may be rewritten in the form

$$I(u,v) = H(u) + H(v) - H(u,v)$$
(14)

This equation includes joint entropy H(u,v), which may be determined on the basis of joint probability distribution, which in turn can be inferred from the joint histogram h(u,v) after appropriate normalization.

Exemplary images from real and corresponding virtual camera are presented in fig.17. This figure also shows values of mutual information as a function of virtual camera position. In the experiment the virtual camera was shifted along the computed navigation path lying in the central part of the airways. Observed local maxima of the mutual information curve are due to bronchial tree vertebras.





8.2. 3D REGISTRATION

Automatic navigation and positioning during medical procedure of transbronchial biopsy requires matching images from bronchoscope camera with data coming from CT examination. Images from bronchoscope camera represent the reflections of light from inside of bronchial tree, however, the CT-data comes from the bronchial tissue density. Since the data are very different (comes from different types of examination) it is very hard correlating it. There is only one common feature of these data - the shape of bronchial tissue. The 2D techniques of navigation make use of this feature in indirect way, that is, by means of 3D rendering of virtual bronchial tree on the basis of CT-data and comparing it with the bronchoscope camera on the basis of direct comparison of 3D structures (shape of bronchial tree). The reference structure could be obtained off-line by means of segmentation of 3D CT-data (see chapter 3). The second structure comes from video data and could be gathered on-line by using *shape-from-shading* [7, 8, 120-124] or *structure-from-motion* [2, 67, 112-114, 125-130] proce-

dures. Finally, the absolute position of bronchoscope camera in the bronchial tree could be determined by correlation of these 3D structures.

Shape-from-shading method is able to extract structure of the object from its projection on still image. The method performs very well on the object illuminated by spot-light (like bronchoscope illumination system), but it could be easily affected by lights reflection and objects texture. Both of these conditions occur in the bronchoscope pictures. Bronchial tissue are highly reflective and posses distinct texture. As an example compare the real image with texture (fig.17b) and the virtual one without texture (fig.17c).

The second method of structure extraction named: *structure-from-motion* is more robust. It makes use of difference between consecutive images from image sequence. The algorithm could be described in a following way:

- Find the optical-flow [111, 131-136] of the image sequence. This is a set (field) of vectors corresponding to the velocity of local texture movement between consecutive images. It can be computed by correlation of pixels blocks or cross power spectrum correlation (making use of 2D FFT) or gradient methods (e.g. wavelet decomposition). Example of two images and optical-flow between them are depicted in fig.18.
- 2) Let's make an assumption: two consecutive images are obtained by one camera pointed to the object at two camera-positions. On the basis of subset of vectors obtained from optical-flow and epipolar geometry, it is possible to determine matrix of rotation R and translation vector T between camera positions. The translation vector is known up to the scaling factor, so the direction of camera movement is known but the velocity is undetermined.
- 3) On the basis of optical-flow, matrices: R, T and epipolar geometry, it is possible to reconstruct 3D object located in the picture. Precision of reconstruction depends on the amount of vectors obtained from optical-flow. Unfortunately, it is not possible to determine dimension of the object. It is known up to the scaling factor. Example of 3D object reconstruction from 2D image sequence is presented in the fig.19.

The procedure could be applied to calculate approximation of bronchoscope camera position or even to determine the precise position of the camera. Our experiments shown, however, it is difficult to obtain reliable results in such a way. First of all, the vectors from *optical-flow* have to be determined with sub-pixel precision. Furthermore, small amount of wrong estimated vectors provide to errors in matrices \mathbf{R} , \mathbf{T} and shape of reconstructed object. In spite of disadvantages mentioned above, the method provides direct comparison of the only one common feature of the analyzed data sets and the obtained results are promising.



Fig.18. Optical flow (c) of two consecutive images (a) and (b)



Fig.19 a) 2D projection of cylinder - view from inside of the cylinder, b) *optical-flow* (vectors have been lengthened by factor of 5 for better legibility), c) 3D view of the original cylinder, d) 3D view of the cylinder reconstruction on the basis of *optical-flow*

9. CONCLUSIONS

CT-based visualization is a popular noninvasive tool for assisting patient's organs examination. Most popular applications are *virtual* bronchoscopy, gastroscopy and angioscopy. Additionally these 3D visualization techniques can be applied in computer-assisted navigation systems supporting physician during endoscope intervention (e.g bronchoscopy, gastroscopy). Emerging application of such systems is the inspection of human body by autonomous mobile robots replacing endoscope, what is recently the challenging issue under development.

In this tutorial paper we have presented the necessary building blocks for bronchoscope navigation system used during computer-assisted transbronchial biopsy. The presented image processing algorithms have to operate on pre-registered huge amounts of data from computed-tomography, and in real time during biopsy on video stream from bronchoscope camera. Thus, the demand for software and hardware efficiency is very high. The presented complete navigation system, after successfully passing the stage of simulation tests, is currently implemented as a real-time system.

The paper provides extensive references in the field of signal processing applied in computer assisted medical intervention. That includes acquisition and reconstruction of CT data, segmentation of anatomical structures, 3D rendering, correction of endoscope camera distortions, navigation in virtual bronchial tree, estimation of bronchoscope egomotion, and 2D, 3D image registration.

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WYBRANE ZAGADNIENIA PRZETWARZANIA OBRAZÓW I SEKWENCJI WIDEO W ZASTOSOWANIU DO KOMPUTEROWEGO WSPOMAGANIA ZABIEGÓW MEDYCZNYCH NA PRZYKŁADZIE BIOPSJI PRZEZOSKRZELOWEJ

Artykuł opisuje wybrane zagadnienia z zakresu przetwarzania sygnałów dotyczące projektu systemu nawigacji końcówki bronchoskopu w trakcie zabiegu z wykorzystaniem technik dopasowania obrazów. Zawarto w nim podstawy teoretyczne omawianych problemów oraz szeroki przegląd literatury, a także przykłady zaczerpnięte z oryginalnych prac autorów. Omówiono algorytmy rekonstrukcji, segmentacji i wizualizacji danych CT (*computed tomography*). Podstawą system nawigacji jest ciągłe porównywanie obrazów z dwóch źródeł: kamery bronchoskopu i wirtualnego drzewa oskrzelowego wizualizowanego na podstawie danych CT. W przypadku, gdy obraz wirtualny jest podobny do obrazu rzeczywistego przyjmuje się, że kamera bronchoskopu w drzewie oskrzelowym ma tę samą pozycję co kamera wirtualna w danych CT. W artykule omówiono następujące aspekty projektowe systemu nawigacji: rekonstrukcję drzewa oskrzelowego z danych CT, korekcję zniekształceń kamery bronchoskopu, szybką estymację ruchu własnego bronchoskopu oraz dopasowanie obrazów rzeczywistych i wirtualnych w przestrzeni 2D i 3D.