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Human Identification Based on Movement Dynamics

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***Abstract**: The interest in identification and verification systems has been recently increased in connection with the increased society requirements and acts of terrorism. The existing access control systems in the market suffer from various drawbacks and often prove to be embarrassing and intrusive for the users. That is why in the last years attention has been focused on biometric person identification which has serious underlying theoretical methodology and produces excellent results due to the availability of powerful computing equipment. A survey of accessible approaches in motion tracking for verification purposes is presented.*

Keywords: *human biometric identification, motion tracking, verification system.*

1. Introduction

Human identification is getting more and more important in the area of access – control systems because of the fast development of the information technologies. Verification is needed when access for specific premises, documents, information, databases, etc. has to be granted to certain individuals. For this purpose, passwords, codes or cards are widely used. However, these means are easy to counterfeit and also people can share the access.

The *biometric person identification* methods provide a way to avoid this. They measure people's biologic characteristics without the necessity of remembering words or numbers. Accessible, cheap, and technically advanced media for collecting sensor information, powerful computing, various software, theoretical achievements in image processing, and practical skills in this area make it possible to measure non-intrusively, digitize and process all sorts of biometric information in real-time. All this makes the biometric information technologies an important and attractive research area and allows developing new identification and verification systems.

Depending on the character of the information used, these techniques can be divided into *physiological* (fingerprints, hand shape, face, iris, voice, etc.) and *behavioral*, the latter being less studied. They comprise analysis of specific human activities such as speaking, gesturing, signing, writing, walking, and typing.

The purpose of this paper is to survey the existing object and people tracking methods in order to realize identification based on *movement dynamics*. It includes the dynamic behaviour of the whole human body as well as of its different parts like face, hands, fingers, legs etc. Features for further verification are extracted using position, velocity and acceleration of the tracking object's parts.

2. Tracking moving objects

Object tracking in a sequence of images is the essential image processing technique for studying the dynamic behaviour of the objects. The frames containing the consecutive object positions are obtained with one or more cameras, which are static or moving. Tracking results are mathematically analysed to describe movement dynamics. Different techniques exist for describing the objects movement, they can be classified according to the character of the measured information on the one hand, or the object concerned on the other.

2.1. Object tracking with velocity/optical flow

Optical flow represents a displacement vector field in the image plane induced by the motion of objects, by the observer or both. Optical flow methods can be divided to three groups [4]: differential methods – they compute image velocity with spatio-temporal derivatives of the intensity; frequency methods – they use information about the energy and phase in the image spectrum; matching methods – they calculate the displacements of tokens matched in small series of images. The gradient constraint equation is:

(1) $$\nabla I(\vec{x}, t) \cdot \vec{v} + I_t(\vec{x}, t) = 0 ,$$

where $\vec{v} = (\frac{dx}{dt}, \frac{dy}{dt})^{\mathrm{T}}$, $\vec{x} = (x, y)$, $I_t(\vec{x}, t)$ denotes the partial time derivative of $I(\vec{x}, t)$, $\nabla I(\vec{x}, t) = (I_x(\vec{x}, t), I_y(\vec{x}, t))^{\mathrm{T}}$ is the spatial intensity gradient and $\nabla I \cdot \vec{v}$ denotes the usual dot product.

Two algorithms, one for estimation of velocity/optical flow and one for estimation of acceleration are described in [16]. They give a unified hierarchical approach to time sequence processing. The basic operation is spatio-temporal filtering with polar separable 3D filters (two spatial dimensions and time). To estimate velocity in an image sequence, a 3D orientation estimation in the sequence is accomplished giving the spatial orientation and the optical flow. The estimation of acceleration improves the capability to track and discriminate moving objects.

In [26] a simple algorithm is presented for selecting and linking interesting flow vectors across a sequence of frames for computing motion trajectories. Tracking of tokens, which have both interesting grey level values in the spatial domain and in the optical flow field in the temporal domain, is realized. In this way, some redundant trajectories are effectively removed. The flow vectors are put together into motion trajectories. Several selected points can be tracked. The candidate points for comparison are obtained by measuring the differences between a certain part of the image and its neighbourhood. A *Kalman* filtering approach is used for smoothing the trajectories. It also deals with the occlusion of feature points. Isolating the trajectories into sets belonging to individual objects should be made before any type of shape or motion interpretation. Therefore, a simple algorithm for segmenting motion trajectories is also presented.

A new technique for tracking of parametric objects, the Dynamic *Velocity Hough Transform*, is described in [21]. It processes the whole image sequence, gathering global evidence of motion and structure. The method tries to find an optimal, smooth trajectory in the parameter space with maximum energy. The authors claim that the standard *Hough Transform* performs robustly in noisy environments and in situations of occlusion. The *Velocity Hough Transform* takes advantage of temporal and structural information simultaneously, by incorporating motion in the evidence. The criterion is that the motion must be smooth in velocity and direction, and the trajectory must pass through the points with the maximum peak.

2.2. Correspondence (feature-based) techniques

The goal of the *feature-based* tracking methods is to discriminate the moving features from the static ones and to calculate the point correspondences in a sequence of images. The correspondence techniques are based on tracking pixels and tokens – point, line or region. The displacement of the objects between successive frames can be relatively large.

Rigid and no polyhedral object tracking in a monocular image sequence without *a priori* knowledge about the objects and camera motion is realized in [7]. It is a contour-based tracking algorithm, where an iterative prediction of the contour location in the next frame is used. The tracking of curved objects can make use of *Active Contour Models* – "snakes", since extraction and tracking are performed at the same time. The drawbacks are in the excessive warping capabilities making the snake attracted by another contour different from the homologous one if the environment is too complex. The aim of the proposed algorithm is to preserve approximately the shape of the snake during its evolution. The function to minimize is:

$$E(v) = -\int_0^1 |\nabla I(s)|^2\, ds + \int_0^1 \alpha\, |v'(s)|^2\, ds + \beta\int_0^1 \left\| v''(s) - v''_0(s) \right\|^2 ds, \tag{2}$$

where $s \to v(s)$ is the parameterization of the snake, $s \to v_0(s)$ is the parameterization of the initialization curve, α is a measure of the elasticity and β is a measure of the stiffness of the snake. In case of rigid objects the contours vary slowly from one frame to another so the search for homologous contours must be based on strong similarity of their curvature.

The paper [22] concerns the object tracking with occlusion prediction using multiple feature correspondences. During total occlusion, the object position is estimated by *Kalman* filter prediction, applied for the movement before the occlusion. The tracking region is defined by a set of point features, tracked using *Kanade–Lucas–Tomashi* algorithm [27]. The problem is to minimize the *dissimilarity* between two windows, one in image *I* and another one in image *J*:

(3) $$\varepsilon = \iint_W [J(A\vec{x} + \vec{d}) - I(\vec{x})]^2 \omega(\vec{x}) d\vec{x} ,$$

where W is the given feature window, $\vec{x} = (x, y)$, the displacement $\vec{d} = (d_x, d_y)$, A is a sum of deformation and identity matrices and $\omega(\vec{x})$ is a weighting function. This algorithm selects optimal features that can be tracked effectively. That is why the tracking is linked with the feature extraction. If a feature is lost in a frame, it is substituted by another one, which keeps their number constant.

An object tracking system is described in [2], robust to a number of ambient conditions, which often severely degrade performance (partial occlusion, photometric changes, incorrect edge matching). The object is described at a number of levels; at each level there is a model/hypothesis for which multiple measurements are available. The multiple measurements make possible the verification of the hypothesis and the outlier identification and removal. The object is described by a set of related geometric primitives (lines and conics). At a low level the primitives are associated with a set of high contrast edges, and are used for rejecting outlying edges in the image. At a high level the primitives are associated with the object pose and are used to reject outlying models.

3. Human body tracking

The human motion analysis [1, 13] is based on the assumption that the body movement can be considered as a movement of articulated objects. The study of such motion is related to kinematics, which is concerned with the geometry of the object and evaluation of its position, orientation and deformation. The whole body tracking is used for automated surveillance and study of human activity.

3.1. 2D methods

The 2D human tracking methods are appearance-based (using texture, color, shape, etc.) or model-based (using preliminary information about the motion). Here one camera is used for the image sequence capture.

A probabilistic multiple-hypothesis framework for tracking articulated objects is described in paper [10]. The probability density of the tracker state is represented as a set of *modes* with *Gaussians* characterizing the neighborhood around them. The temporal evolution of the probability density is achieved through sampling from the prior distribution and by local optimization of the sample positions to obtain updated modes. The proposed algorithm is modularized compatibly with *Bayes Rule*:

(4) $$p(x_t \mid Z_t) = kp(z_t \mid x_t)\, p(x_t \mid Z_{t-1}) ,$$

where x_t is the tracker state at time t, z_t is the observed data, Z_t is the aggregation of past image observations and k is a normalization constant. The first stage of the algorithm is the generation of the new prior density $p(x_t \mid Z_{t-1})$ by passing the modes of $p(x_{t-1} \mid Z_{t-1})$ through the *Kalman* filter prediction. Then, a likelihood computation is accomplished, involving creation of initial hypothesis by sampling the distribution of $p(x_t \mid Z_{t-1})$, refinement of the hypothesis through differential state-space search for obtaining the modes of the likelihood $p(z_t \mid x_t)$, and measure of the local statistics associated with each likelihood mode using perturbation analysis. The last stage is computation of the posterior $p(x_t \mid Z_t)$ density according to *Bayes Rule*, update and selection of the set of modes. This method for hypothesis generation from state-space search does not require the use of discrete features.

A real-time system for tracking people and interpreting their behavior is presented in [30]. A multi-class statistical model of color and shape is used to obtain a 2D representation of the body in a wide range of conditions. The system applies a *Maximum A Posteriori Probability* approach to detect and track the human body. The body is modeled with blobs, described statistically with spatial and color (*YUV*) gaussian distributions over the pixels (Fig.1). Statistical model is also built for the background. In the initialization stage, the system learns the scene without the presence of a person in it. After its appearance, the creation of the model starts. Tracking is related with prediction of the person's appearance in the next frame using the current state of the model. The system is robust to occlusions and dark shadows.

Fig. 1. Video input (left), segmentation (center) and 2D representation of the blob statistics (right) [30]

3.2. Pseudo-3D methods

A certain part of the human body tracking methods use only one camera, but build 3D human model. They can be called *pseudo-3D methods*.

Paper [8] demonstrates a new motion estimation technique, able to recover high degree-of-freedom articulated human body configurations in complex video sequences. The number of the free parameters is reduced considerably because human parts do not move independently. Authors claim that the twist and product of exponential maps formalism for kinematic chains is a convenient way to describe these additional constraints. The *twist* representation is based on the observation that every rigid motion can described as a rotation around a 3D axis and a translation along it. A twist ξ has two representations: a 6D vector or a matrix:

$$\xi = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}, \text{ or } \hat{\xi} = \begin{bmatrix} 0 & -\omega_z & \omega_y & v_1 \\ \omega_z & 0 & -\omega_x & v_2 \\ -\omega_y & \omega_x & 0 & v_3 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \tag{5}$$

ω is a 3D unit vector that points out to the direction of the rotation axis. The amount of rotation is specified with a scalar angle θ that is multiplied by the twist: $\xi\ \theta$. The movement of a body segment can be described as motion of the previous segment in a kinematical chain and an angular motion around a body joint. This adds only one degree of freedom for each additional segment in the chain. If we have a chain of K+1 segments linked with K joints and describe each joint by a twist ξ_k, a point on segment k is mapped from the object frame into the camera frame depending on $G_0 = e^{\hat{\xi}}$ and angles $\theta_1, \theta_2, ..., \theta_k$:

(6) $$g_k(\theta_1, \theta_2, ..., \theta_k) = G_0 \cdot e^{\hat{\xi}_1 \cdot \theta_1} \cdot e^{\hat{\xi}_2 \cdot \theta_2} \cdot ... \cdot e^{\hat{\xi}_k \cdot \theta_k}.$$

This is called the *product of exponential maps* for kinematic chains. The exponential maps allow to relate the image motion vectors linearly to the angular velocity. As a result simple linear systems are solved, which makes it easy to recover robustly the kinematical degrees of freedom in presence of noise and complex self-occlusion configurations. The human kinematical model is presented with blobs.

A hierarchical model of human dynamics for representing independent human body tracking in monocular video sequences is proposed in [20]. The model is trained by real data collected from a group of people. The kinematics is encoded using Hierarchical *Principal Component Analysis* and dynamics – using *Hidden Markov Models*. The top of the hierarchy contains information about the whole body, and the lower levels contain more detailed information about the possible poses of the body's subparts (Fig. 2). The model is able to recover 3D human body skeleton from 2D image sequences.

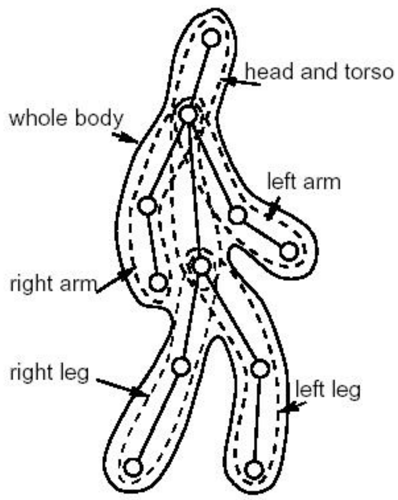

Fig. 2. Hierarchical model of a person [20]

3.3. 3D methods

To enlarge the view field and increase the number of points of view, two or more cameras, placed in different positions and working simultaneously can be used.

A visual system for 3D unconstrained model-based human motion tracking is presented in [14]. A 3D human body pose is recovered in each moment using image sequences obtained simultaneously from several view points without the use of markers. The problem of pose recovery is formulated as a search problem and is related to finding pose parameters of a graphical human model whose synthesized appearance is most similar to the actual appearance of the real human in multi-view images. The similarity measure between model view and actual scene is based on arbitrary edge contours. A robust variant of *chamfer matching* is used. The directed chamfer distance DD*(T,R)* between the test point set *T* and reference point set *R* is the sum of the distances between each point from *T* to its nearest point in *R*:

$$\mathrm{DD}(T,R) = \sum_{t\in T} dd(t,R) = \sum_{t\in T} \min_{r\in R} \|t-r\| . \tag{7}$$

The models used are acquired from the images.

A method for human motion estimation using two or more static cameras is proposed in [12]. The technique copes with fast movements, self-occlusion and noisy images. The goal is to analyze the human gait for identification purpose based on the study of 3D model parameters variation. For gait analysis not only recovery of the general location and orientation of the body is needed, but also the pose of the legs and arms. A 3D articulated human body model is used. The authors compare the model projections on the images to the detected silhouettes of the person and this moves the model towards the final estimation of the real pose.

Paper [19] concerns the tracking of human body parts using multiple black-and-white cameras. The proposed method uses information from the contours. As a result, 3D positions and orientations of the subject's body parts are obtained and so trajectories, velocities and accelerations can be calculated. The system has a visualization part where the estimated motion parameters are animated with a customized physic-based graphical model. The person can move without wearing markers, but the background is assumed to be static.

4. Tracking human body parts

In many cases the study of the movement of specific body parts such as face, hands, fingers, legs etc. is needed. In biometrics the former is necessary for the identification of the body parts and the interpretation of human behavior. The visual motion dynamics estimation methods concerning human limbs and wrist are getting more and more popular.

4.1. Tracking limbs

Human limbs can be modeled as a system of rigid objects connected with articulations with one or more degrees of freedom. In case of tracking, markers are often used, being easy to recognize, and constant background is assumed. Many applications are developed in the area of security, motion estimation of physical exercises, etc. [28].

In [29] an approach is presented aimed at the study of cyclic motion of the human body. The specific knowledge of structure and motion of the body is formulated as a 3D kinematical model. The person's leg is tracked, the upper joint of the hip being considered fixed. The parts of the leg are represented with cones. The cycling action between two consecutive frames is decomposed into a set of 3D instantaneous motion parameters. An iterative method is used for estimation of these parameters by minimizing a goodness-fitting criterion without explicitly computing optical flow. The criterion is based on the measurement of displaced frame differences assumed to be induced by motion of joint objects. In the next stage cyclic motion tracking in a long image sequence is realized, for which a procedure based on a prediction-compensation scheme is designed for detecting variations in the intensity caused by noise.

The problem of tracking the human arm in 3D is addressed in [15]. The simplest formulation of the task is used, with one black-and-white camera and without the use of markers. The upper and the lower arms are modeled as truncated right-circular cones, and the shoulder and elbow joints are modeled as spherical joints (Fig. 3). The hand is captured on a dark background, after which threshold and blurring with gaussian filter is applied to the obtained images. The difference between the real image and the image predicted with a *Kalman* filter is calculated. It is used for recursive error estimation and correction of the dimensions and orientation of the model.

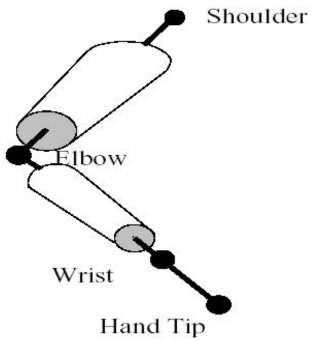

Fig. 3. Volumetric arm model [15]

4.2. Wrist tracking

Wrist tracking is related to machine control with hand gestures, translation of gesture alphabets, automated signaling, etc. [23]. For the hand position determination, an elimination of the background or skin color detection can be used. The interpretation of gestures is achieved by analysis of hand shape and motion.

Paper [25] describes a system for tracking a model of the human wrist with 27 degrees of freedom (Fig. 4). Line and point features, extracted from black-and-white images, are used for tracking. No markers or gloves are used. The model is composed of two parts – kinematical, which comprises all possible spatial positions of the articulated objects, and feature model, describing the image appearance of each link shape. Kinematics is modeled with *Denavit-Hartenburg* presentation, often used in robotics. The hand is presented with 16 rigid parts – three for each finger and one for the palm. The features (lines and points) are generated from the projection of the hand model in the image plane. The finger parts are modeled as cylinders and their joints – as cross points of the cylinders' central axis.

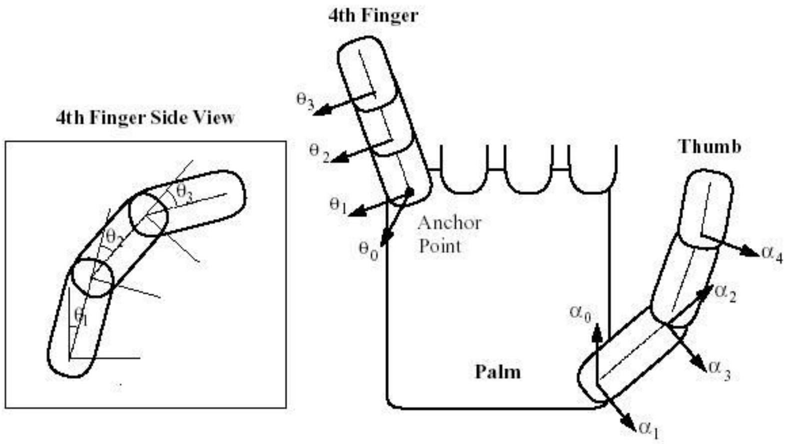

Fig. 4. Kinematic models, illustrated for forth finger and thumb [25]

In [17], a system for hand tracking and gesture recognition is presented. Tracking is achieved using 2D deformable *Active Shape Models* (smart snakes) and genetic algorithm is used to perform an initial global image search. The *Point Distribution Model* used provides a generic flexible model that can be used to track any 2D deformable object. The system is only capable to track an open hand, but works in real-time and copes well with cluttered backgrounds and variation in lighting conditions.

4.3. Analysis of specific gestures

The main approaches for human gesture analysis are glove-based and vision-based. *Glove-based* devices employ sensors attached to a glove that transforms the finger flexion into electric signals for the determination of the hand posture. The *vision-based* analysis is more natural; it is realized with cameras and solves difficult problems like moving hand segmentation, hand position tracking and gesture recognition. For easier interpretation, sometimes models, markers, uniform background or restricted set of gestures for recognition, are used.

An application is presented in [5] which controls a computer with hand gestures while giving a presentation. To use the system the user has to wear a glove. He can issue commands by pointing at the active zone (a projection of the screen on a wall, where a cursor appears) and by performing gestures. By means of 16 gesture commands, the user can navigate pages or slides, highlight parts of the screen, etc. Each gesture command is characterized by a start position, dynamic phase and end position. The command recognition involves detection of the intention to address a command to the system (the projection of the hand has to be in the active zone), segmentation of gestures (recognition of start and end positions), and classification (recognition of a gesture using its dynamic phase). Gestures that are not recognized are ignored. The wrist orientation and finger positions are quantized in order to make positions both easier to recognize and use. The dynamic phase uses the hand projection path, the rotation of the wrist, the movements of the fingers, and the variation of the distance between the hand and the active zone.

Paper [11] presents a model-based method for recognizing human-hand gestures. A finite state machine is used to model four qualitatively distinct phases of a generic gesture. First, the hand has to be in initial position (open, with upright fingers and the palm – in direction to the camera; "hello" position). Next, the user moves the fingers or the entire hand to the gesture position. The user keeps the hand in gesture position for desired duration of gesture command and then moves smoothly the hand back in the initial position. The fingertips are marked; they are detected with histogram segmentation and tracked in a sequence of images for motion trajectories computation. These trajectories are then represented by the initial and end position of each finger as vectors. The vectors are compared to the stored vectors-models. As a result, the recognition of seven specific gestures is presented.

5. Conclusion

Human motion tracking has many applications in the area of human-computer interaction, security, biometrics (human identification based on movement). Concerning the identification based on movement dynamics, most convenient for research are the human movements when signing, because each signature is unique. A question of present interest is the realization of online identification, so the optical methods for signature tracking and recognition are an important topic for further investigations. Even if a signature can be counterfeited, the most secure way to avoid this is provided by the writing person's hand motion estimation.

Many difficulties may appear due to the environment and light conditions. Some of these problems are still unsolved. A detailed study of the segmentation methods is necessary as well as contour line description, point alignment from corresponding lines in a sequence of images, obtaining of detailed information from the motion trajectories, measurement of dynamic parameters, estimation of the information rate of different features, attainment of reliable verification, etc.

The study of human dynamics application to the development of access-control systems is a new research area and the number of published papers is relatively small. Besides, the obtained results are not always published due to the confidentiality aspects of the subject. Nevertheless, the anticipated potential of biometrics and its not disturbing data acquisition possibilities attracts the attention of more and more researchers and institutions all over the world. As a result, a few large projects supported by the European Community have been launched lately.

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