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A Robust Face Tracking Method by Employing Color-based Particle Filter

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Abstract: *Human or face tracking in a diverse environment is very important for various applications in computer vision, especially for video surveillance. Usually, a color cue offers many advantages over motion or geometric information which cannot robustly handle partial occlusion, rotation, scale and resolution changes. In this paper, we present a robust face tracking system by employing a color-based particle filter. The face detection technique is realized based on a Haar-like features algorithm. Here we exploit skin color cues for face-tracking, and it also proposes a body-part particle distribution system. This system is robust against occlusion by human or others and it can perform the tracking in real-time. We conducted experiments in both indoor and outdoor environments, with either a single or multiple persons in a view. Based on the color-based and body-part particle filter, we tracked a person's face satisfactorily by a developed simple robot system.*

Keywords *Human tracking, particle filter, face tracking, color cue.*

1. Introduction

Human motion analysis can be typified into three broad areas, namely – human motion and activity recognition, human tracking and human body structure analysis [3]. In this paper, we concentrate on human motion tracking. Tracking is a difficult task in computer vision and other fields. Motion tracking, face tracking or person/object tracking are very crucial in video surveillance, motion understanding, computer-robot interaction, perceptual user interfaces, smart rooms, object-based video communication/compression, driver assistance, and related application arenas [26]. There are various approaches on human motion tracking to understand the behavior of a person or to realize video surveillance. Various methods have been employed for better tracking by considering various dimensions, for example, partial occlusion [9,11], clutter or complex background [8,17-18], multi-target tracking [11-13], change in illumination, abrupt motion of the face, skin-colored background, scale variations, etc. [4-7] by employing color-based particle filter [15]. Here we exploit the skin color as the cue for face tracking. Some low level features e.g., color, motion, contour, depth information to the tracked object, face, etc., are usually used for general tracking methods [17].

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In this paper, we consider color information due to the fact that color cue is easy to implement and insensitive to the variation of pose, expression, scale, and rotation. It has been used in most face tracking processes and yields a high recognition rate [4]. We present the detailed description in the following section.

The paper is organized as follows: Section 2 illustrates the related work. In Section 3, we present a color-based tracking system employing particle filter [15]. Experimental systems are covered in Section 4, which followed by the results and analysis in Section 5. We conclude the paper in Section 6.

2. Related Work

There are some good surveys on human motion analysis [1-3]. There are several other approaches using cues other than color cue and considering multiple cues for tracking. Triesch and Malsburg [25] integrated five different visual cues to detect and track a single face by calculating the weighted sum of each cue's observational probability. In particular, discordant cues are quickly suppressed and recalibrated, while cues having been consistent with the result in the recent past are given a higher weight in the future. Wu and Huang [27] combined the color cue and the face contour on the basis of edge detection to increase the robustness and generality, though this method is time-consuming and often fails to track the face in a skin-colored complex background due to detection error of the face contour.

In another approach, Comaniciu et al. [26] derived a simple representation of the background features and used it to neglect the background features in the target model and in the target candidate region extracted for target localization phase. Yin and Collins [8] also proposed a spatial divide-and-conquer method to discriminate the target from the background. These techniques are effective when the background is simple but their performance is poor whenever some objects or elements of the background have similar features to the target.

Kalman Filter and its variants (e.g., Extended Kalman Filter, Unscented Kalman Filter (UKF)), CONDENSATION algorithm [6], Particle Filter with its variants, etc. are employed for tracking an object in various conditions. Temporal Bayesian filtering (e.g., CONDENSATION) is one of the most successful object-tracking methods. Variants of Kalman filters are limited by their Gaussian assumptions. UKF uses a set of discretely sampled points to parameterize the mean and covariance of the posterior density. We can also apply Hidden Markov Models (HMM) filters for tracking if the state space is discrete and if it consists of a finite number of states.

Bagnato et al. [16] proposed a new extension of the CONDENSATION algorithm, based on Active Appearance Model (AAM) with application to infants face tracking. They addressed the problem of tracking a face and its features in baby video sequences. A mixed state particle filtering is proposed, where the distribution of observations is derived from AAM.

One of the most popular methods for object tracking is the Particle Filter, since it achieves good performances in all cases including those where the target is partially occluded or several distracters appear in the scene [18]. Particle filter can be regarded as a hypothesis tracker that approximates the filtered posterior distribution by a set of weighted hypotheses called particles (i.e., a set of random samples). This technique gives weights to the particles based on a likelihood function and distributes them according to a motion model. When the particles are properly placed, weighted and propagated, posteriors can be estimated sequentially over time. Particle filters are based on Monte Carlo integration methods. The current density of the state is represented by a set of random samples with associated weights and the new density is computed based on these samples and weights.

Despite the uncertainty in the visual appearances, frontal faces have a similar image pattern that allows the use of the Haar features for face detection [10]. Particle filter is used for tracking based on the mean field Boltzmann model, which is robust against partial occlusion [9]. Motion Adaptive Weighted Unmatched Pixel Count (MAWUPC) algorithm that incorporates multiple cues to track the face in the complex background and face-occluded environment was proposed by [17]. This incorporated color and motion cues and then particle filter is employed for tracking. Li and Chua [14] proposed a transductive color-based particle filter algorithm to address the problem of non-stationary color distribution in color tracking. The use of particle filtering [15] allows us to handle color clutter better in the background, as well as occlusion. By employing multiple hypotheses and a dynamic system model, the particle filter approach can track objects under cases of clutter and occlusion. Nummiaro et al. [15] used color histogram to represent color distribution.

3. Tracking Methodology

This section describes in detail the color-based particle filter method because we exploited a color-based particle filter system. In this paper, we introduce a body-part particle distribution concept to make the system robust against occlusion. A target is tracked using a particle filter by comparing its color histogram with the histogram of the sample positions using the Bhattacharyya distance measurements [15]. This is a *top*-down approach where it generates object hypotheses and tries to verify them using the image [20]. In this section, we present the color-based particle filter [20], where the weighted sample set is,

$$S = \left\{ \left(\mathbf{s}^{(n)}, \pi^{(n)} \right) \mid n = 1 \ldots N \right\} \tag{1}$$

where S is the particle set, and π is the weight. The size of the sample set is N. Then $\mathbf{s}$ is one hypothetical state of the object (and $\mathbf{s}$ can be referred to as a *sample*) with a corresponding discrete sampling probability π (a numerical weighting factor), where

$$\sum_{n=1}^{N} \pi^{(n)} = 1.$$

The evolution of the sample set can be described by propagating each sample according to a system model. Each element of the set is weighted in terms of the observations $\{z_1, \ldots, z_t\}$ up to time t and N samples are drawn with replacement by choosing a particular sample with probability,

$$\pi^{(n)} = p\left(z_t \middle| X_t = s_t^{(n)}\right)$$

The mean state of an object is estimated at each time step by,

$$E[S_t] = \sum_{n=1}^{N} \pi_t^{(n)} \mathrm{s}_t^{(n)}. \tag{2}$$

As a target model, we use color distributions. Color distributions achieve robustness against non-rigidity, partial occlusion-, scale- and rotation-invariants [21-22]. However, color is sensitive to the variations in the light source. Suppose that the color distributions are discretized into m-bins or clusters. Color distributions represent histograms of the pixel values. The histogram is produced with the function $h_H(\mathrm{x}_i)$ - that assigns the color at location x_i to the corresponding bins. In this paper, we consider HSV color space instead of RGB color space due to the fact that the former is less sensitive to lighting conditions with less sensitivity to V, hence we achieve 8x8x4 bins. Color-distribution is used for face tracking likelihood. In an object tracking model, a rectangle with H_x and H_y as the half-width and half-height of the rectangle (Fig. 1), having the center of the rectangle as (x_i, y_i) is considered.

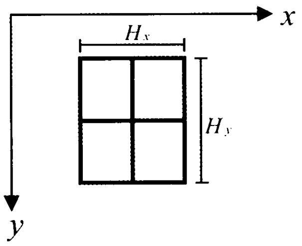


Fig.1. Rectangular dimension for the tracking object.

In this algorithm, when the boundary pixels belong to the background or get occluded, small weights are assigned to the pixels that are further away from the region center by employing a kernel weighting function,

$$k(r)=\begin{cases} 1-r^2 & \text{if } r<1 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

where r is the distance from the region center. This increases the reliability of the color distribution. The discrete color distribution

$$p_{\mathrm{y}}=\left\{p_{\mathrm{y}}^{(u)}\right\}_{u=1,\dots,m}$$

over a region y, using u bins, is defined as,

$$p_{\mathrm{y}}^{(u)}=f\sum_{i=1}^{n_0} k\left(\frac{\|\mathrm{y}-\mathrm{x}_i\|}{a}\right)\delta\left[h_H(\mathrm{x}_i)-u\right] \qquad (4)$$

Here, n_0 is the number of pixels in the region, and $\delta[n]$ is the Kronecker delta function that determines whether the pixel x_i belongs to the bin u or not:

$$\delta[n]=\begin{cases} 1 & \text{if } n=0 \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

The parameter,

$$a=\sqrt{H_x^2+H_y^2}$$

is used to adapt the object's face to the size of the region, and f is the normalization factor,

$$f=\frac{1}{\sum_{i=1}^{n_0} k\left(\frac{\|\mathrm{y}-\mathrm{x}_i\|}{a}\right)} \qquad (6)$$

so that it may ensure

$$\sum_{u=1}^{m} p_{\mathrm{y}}^{(u)}=1.$$

This normalization factor simplifies the search of a good similarity measure between two histograms.

In a tracking approach, the estimated state is updated at each time step by incorporating the new observations. Hence, a quality factor for similarity measure is necessary based on the histograms of color distributions of target model and target candidate. Assume a histogram

$$p_{\mathrm{y}}=\left\{p_{\mathrm{y}}^{(u)}\right\}_{u=1,\dots,m}$$

Be a *target candidate* and a histogram

$$q_{\mathrm{y}}=\left\{q_{\mathrm{y}}^{(u)}\right\}_{u=1,\dots,m}$$

be a *target model*. Though we could use various methods, e.g., Minkowski form distances, Histogram intersection, Mahalanobis distance, Earth mover's distance, etc. for calculating the distance measure, we use *Bhattacharyya coefficient* and *distance* instead due to its fast and simple computation. Fig. 2 demonstrates an example of similarity measures based on skin color of the face. For the two distributions $p(u)$ and $q(u)$, the Bhattacharyya coefficient is,

$$\rho[p,q]=\int\sqrt{p(u)q(u)}\,du.$$

For discrete color histograms p_{y} and q_{y}, it is defined as,

$$\rho[p,q]=\sum_{u=1}^{m}\sqrt{p^{(u)}q^{(u)}}. \qquad (7)$$

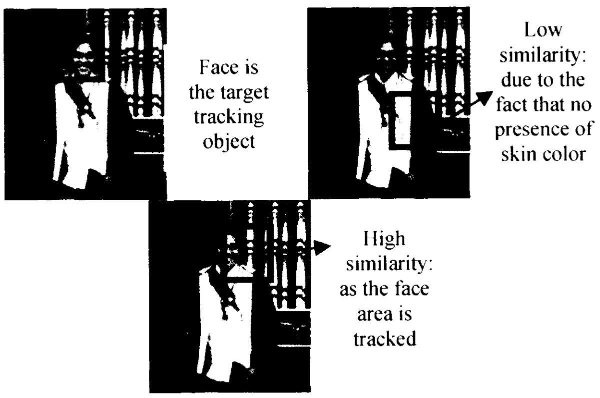


Fig. 2. Example of similarity measures based on skin color of the face. Bottom Figure has high similarity.

As evident, the larger ρ is, the more similar the distributions are and vice versa (See Figs. 2 and 3). Hence, for two identical normalized histograms, ρ = 1 is obtained that indicates perfect match. The Bhattacharyya coefficient calculation between two normalized histograms is based on the count values of single bins indexing the same intensity range in both histograms (in this case, the total number of bins u_{max}= m). The distance between the two distributions can be given as

$$d_p = \sqrt{1-\rho[p,q]}\ .$$

So, it is always positive, symmetric and equals to zero when both distributions are equal. Also, the smaller d_p is, the more similar the distributions are. The tracker in this paper employs this distance measure to update the *a priori* distribution calculated by the particle filter and track the candidate object. Each sample **s** in the sample set S can be scanned as a rectangle and it can be represented as,

$$s = \left(x, y, \dot{x}, \dot{y}; H_x, H_y \right)^T .$$

Here, (x, y) is the center coordinate of the object, $(\dot{x}, \dot{y})$ is the motion parameters of the center coordinates. H_x and H_y are the length of the half axes, and the ratio of the axes is always kept constant for efficient implementation of histogram and similarity measure calculations.

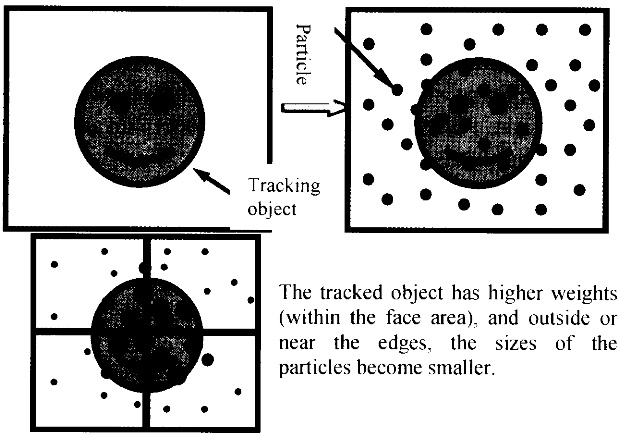


Fig.3. Distribution of particles randomly in the object area. The head is the tracked object. After a while, this area will have more weight.

The sample set is propagated through the application of a dynamic model that defines essentially the expected movement,

$$s_t^{(n)} = A s_{t-1}^{(n)} + B w_{t-1}^{(n)}. \tag{8}$$

where A defines the deterministic component of the model and here it is defined as,

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix};$$

$Bw_{t-1}^{(n)}$ is the stochastic component of this model equation where B is defined as,

$$B = \begin{bmatrix} 1 \\ 1 \end{bmatrix};$$

w_{t-1} is a Gaussian random variable that describes the error source affecting the system model. This Gaussian noise is provided by,

$$w = \sqrt{-2\sigma \ln(r_1)} \sin(2\pi r_2) + \mu. \tag{9}$$

where, σ is standard deviation, r_1 and r_2 are random numbers $r \in [0,1]$, and μ is the mean. Now both target histogram q and the candidate histogram $p_{s^{(n)}}$ are computed from Eq. 4, provided that the target is centered at the origin of the rectangle region.

To start with, we select N samples from the set S_{t-1} with probability $\pi_{t-1}^{(n)}$. The selection allows the samples with high probability to strengthen the set by multiple copies, and deletes the weakest samples. It is based on random sampling and cumulative probabilities of the weight π. So the normalized cumulative probabilities c'_{t-1} are calculated as,

$$c_{t-1}^{(0)} = 0,\ c_{t-1}^{(n)} = c_{t-1}^{(n-1)} + \pi_{t-1}^{(n)},\ c_{t-1}'^{(n)} = \frac{c_{t-1}^{(n)}}{c_{t-1}^{(N)}}.$$

A uniformly distributed random number $r \in [0,1]$ is generated. By employing binary search, we then find the smallest j for which $c_{t-1}'^{(j)} \geq r$. Then we set $s_{t-1}'^{(n)} = s_{t-1}^{(j)}$. This is repeated for all samples. Each sample is propagated and estimated by Eq. 8. Next, the measurements for each propagated sample s of the set S_t are determined. They lead to the weight vector π_t in the observation step.

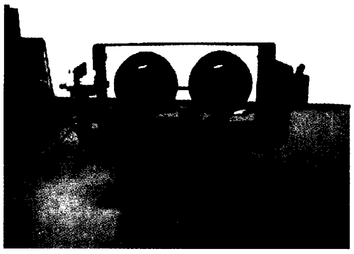
To observe the color distributions, we first calculate the color distributions for each sample of the set S_t using Eq. 4 by replacing y with $s_t^{(n)}$. To establish the relationship between observations and measurements, the Bhattacharyya coefficients are calculated for each sample of the set S_t by using Eq. 7. Here, histograms of each candidate are compared to the target model histogram. We give larger weights to the samples having more similar resemblance to the target model, where the weight of each sample is calculated as,

$$\pi^{(n)} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{d_p^2}{2\sigma^2}}. \tag{10}$$

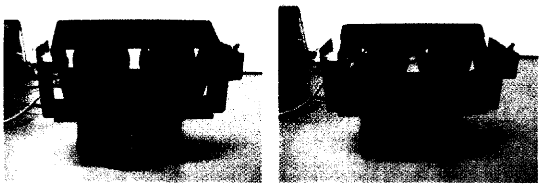
which is specified by a Gaussian with variance σ. This Gaussian weighting increases the importance of the samples with a high Bhattacharyya coefficient, and decreases the ones with a low value.

Note that for easy computation, we need to normalize each color distribution of Eq. 4. Finally, based on Eq. 2, we calculate the weighted mean state $E[S_t]$ to determine the mean state of the new sample set that allows a simple visualization of the results. The mean weight $\pi_{E[S_t]}$ is the weight factor, given by the location of $E[S_t]$. The coordinates x, y and the half-axes of the weighted mean state are now labeled as a new location at step t. Then with $S_t \rightarrow S_{t-1}$, the new iteration step can start.

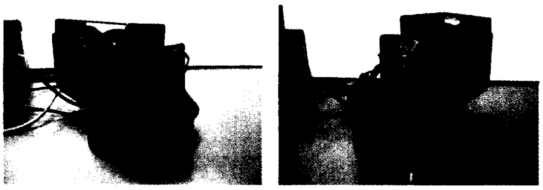
The introduction of a body-part particle distribution concept makes the system robust against occlusion. This is one of the most important components in the proposed method. If we set particles only in face, we find difficulty to track the person continuously if the person is occluded by other object or person. To solve this problem, we divide the body into two parts – face part and upper part of the body without face and based on the color of cloths, we use another particle distribution. Therefore, based on the two particle sets, we can robustly and strongly manage the tracking of the face even in occlusion.



(a) Simple robot head with 2 eyes comprising USB cameras.



(b) Tilt motion: the head is rotating downwards and upwards.



(c) Pan motion: the head is rotating sideways.

Fig.4. The robot head used for the tracking experiment.

4. Experimental System

In this paper, skin color of a face is tracked as well as the upper body cloths' color. For any presence such as hands or other parts of a body, we can easily extract the face area. We assume that a tracked person is wearing normal dress. Face is detected by AdaBoost [24], which is sensitive to noisy data and outliers. This face detection is based on a boosting algorithm which yields good detection rates [24]. This detector is highly inspired by the robust real-time object detection of Viola and Jones [23]. In this work, we employed 100 particles. A simple autonomous robot head is developed for the experiment (Fig. 4). The robot head can perform pan-tilt motion, courtesy to two servomotors installed at the ear position (for tilting motion) and at the center of the neck (for panning motion). Fig. 4(b) and (c) depict the movement of the robot head to upward and to downward direction and rotation to the left and to the right direction. However, it can not perform 360° rotation due to its simplicity. Fig. 5 shows an experimental setup for tracking a single person. The user initializes the target person to be tracked using a USB camera.

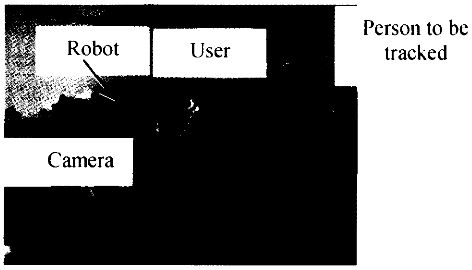


Fig.5. Experimental set-up with the user (sitting), person to be tracked (standing), the robot near the user and the camera.

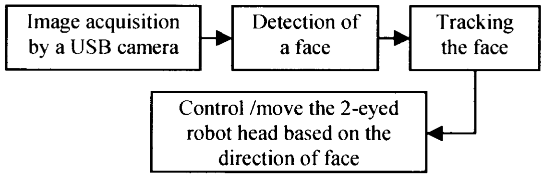


Fig.6. A simplified system flow diagram of the experiment.

Then based on the movement of the target person, the system can track it and hence the robot head (having two USB cameras) can pan or tilt based on the target person's movement. The sequence is illustrated using the flow diagram of Fig. 6. Note that one USB camera is employed to take the video of the movement of the person to be tracked. Two cameras will be employed for wider view of the environment in near future.

5. Result and Discussion

This section will present the result of various tracking experiments based on the above-mentioned algorithms and experimental set-ups. Initially, the system will detect faces of some persons in a video by using the AdaBoost algorithm and will start tracking once the user has specified a particular person by his/her label on the display. Fig. 7 and Fig. 8 (multiple persons) show the tracking results of the face. The program controls the robot head according to the movement and tracking direction of the face, and with some limitations of its degree-of-freedom. Note that is not a multi-camera tracking system. It means only one camera is operating to track the particular person or object. In our experiment, the tracking video is taken from one camera. The developed robot head moves according to the tracking information, like human eyes and shoulder. This robot head is not related to the tracking method – it is developed to demonstrate the tracking output for demonstration.

Fig. 7 illustrates the sequences of images on tracking a single person. The 3rd row shows that hand is rotating in front of the face, and the 5th row shows that the person is behind a screen and then appears. The tracker can track the person satisfactorily.

The red crossing lines point the center point of the detected object or face to be tracked. The tracked person is divided into upper head/face section and lower body parts and denoted by green rectangular boxes. Our concentration is mainly on the upper face green box. The second image of the 5^{th} row of Fig. 7 has two isolated blue rectangles and these shows the searching mode after any occasion of large occlusion.

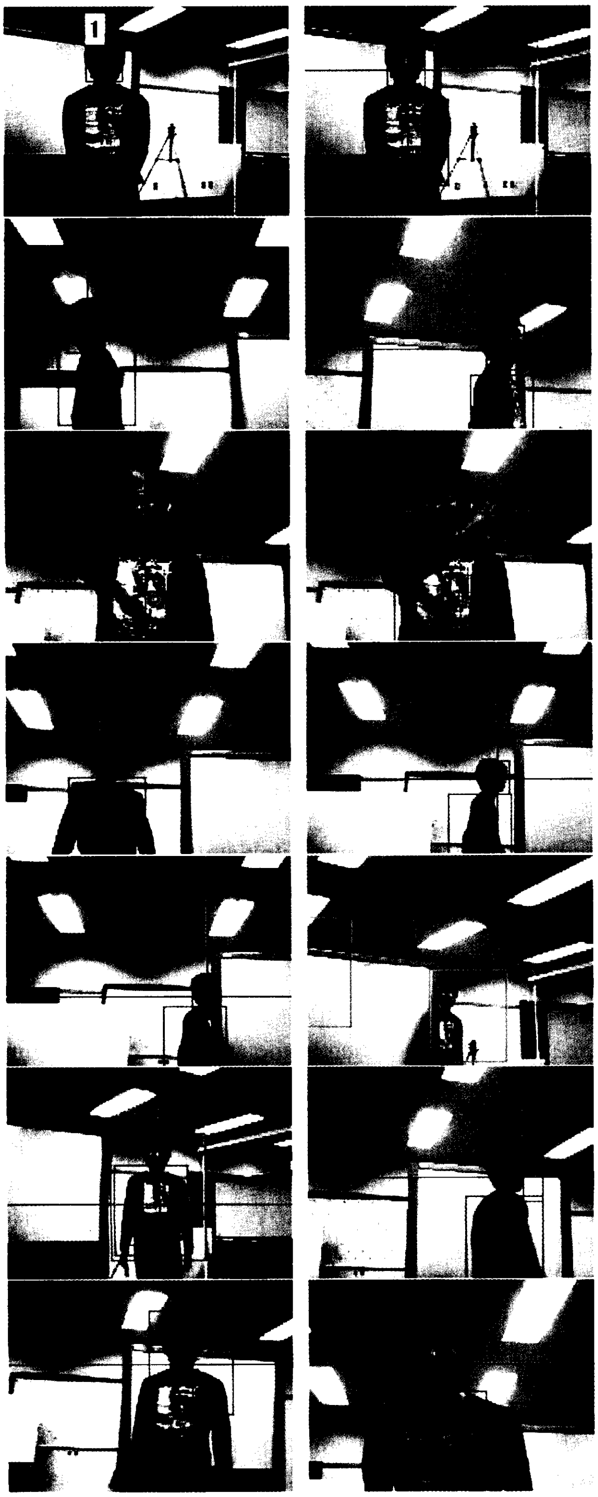


Fig.7. Tracking result of a single person with the presence of occlusion by a screen.

We also track the person with the presence of multiple persons and partial occlusion (Fig. 8). In this case, the person in no. 1 is being tracked with the presence of two other persons and occlusion due to a screen and the presence of two persons. It tracks almost perfectly even though the presence of other people in the view and occlusion. These experiments were done in an indoor environment. In some cases, momentarily, the tracker failed to track due to full occlusion by another person.

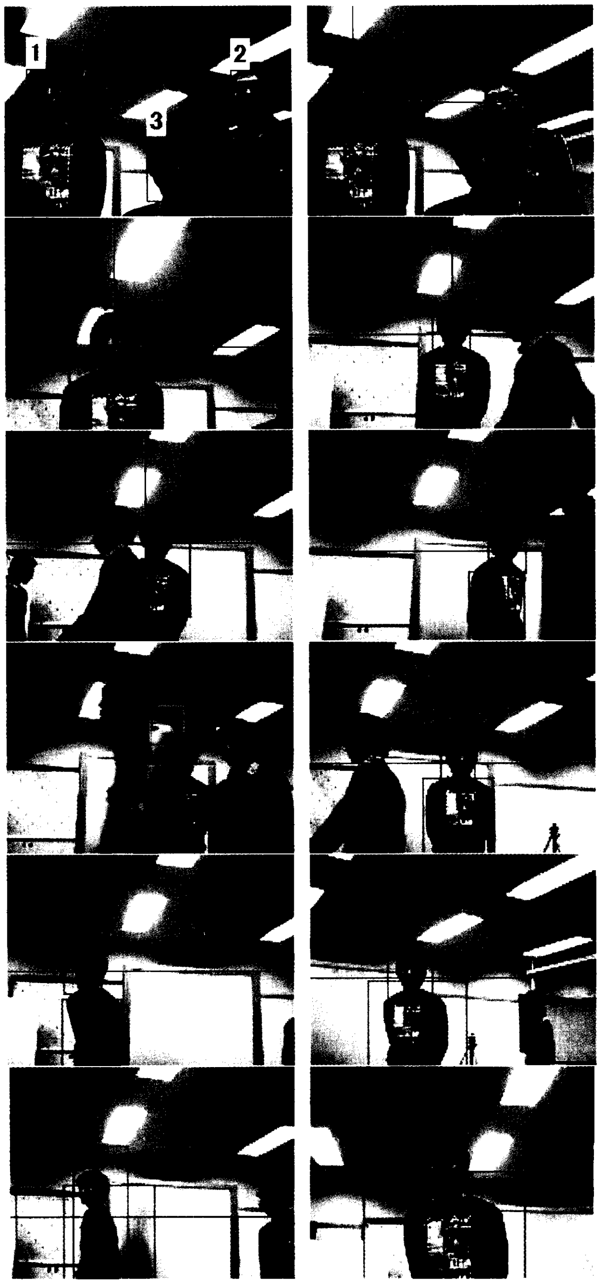


Fig.8. Tracking results of a person among multiple persons and partial occlusion.

So far, the tracking experiments were performed indoor with usual illumination. We have done the experiment outdoor as well with the presence of multiple persons and partial occlusions (Fig. 9). The tracking results were quite satisfactory. Here, if a person's face and/or upper body-part are occluded by another person's face or body-part or by other objects (e.g., screen in this case), sill the method can track. Also, the person can be tracked even when a person faces the opposite side. However, this method can be stronger if the face can be detected even when the face is facing the opposite direction of the camera.

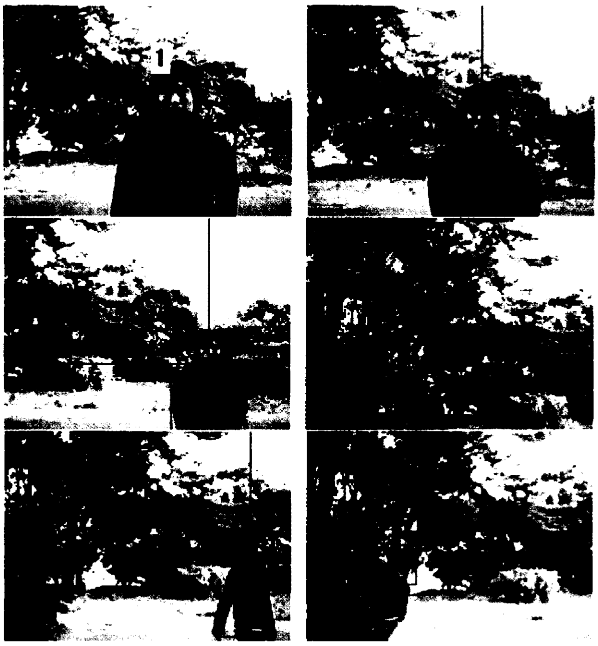


Fig.9. Tracking a single person outdoor.

6. Conclusion

In this paper, we have proposed a robust tracking method by employing a particle filter based on color cues on a face and on an upper body part. This concept of body-part inclusion along with the face area based on color cues is a significant improvement in tracking persons in diverse environments and in the presence of occlusions. The method has been experimentally tested with a robot head that can move based on the movement of the tracked person – both indoor and outdoor environments, with and without the presence of multiple persons in a view. Color cue is widely used for various tracking methods, but it has some limitations, especially due to the variation of the illumination changes and the presence of related color cues in the environment. Hence, for a robust tracking methodology, we need to consider multiple cues for tracking with the constraint of complexity in mind. Moreover, based on this method, a better robot-head or a full robot can be developed so that an intelligent system can automatically track a person and take the necessary actions. Our research tracks a single person in different environments. Therefore, it is inevitable to develop a robust system that can track a single person as well as multiple-persons. Moreover, two cameras will be employed for wider view of the environment in near future so that tracking and surveillance can be achieved in a better manner. Hence, we need to improve the tracking system for real-life surveillance in future.

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References

[1] Ahad, Md. Atiqur Rahman, Tan, J.K., Kim, H. and Ishikawa, S. (2010): "Motion History Image: Its Variants and Applications," Machine Vision and Applications, pp. 1-27.

[2] Ahad, Md. Atiqur Rahman, Tan, J.K., Kim, H. and Ishikawa, S. (2008): "Human Activity Recognition: Various Paradigms," Int. Conf. on Control, Automation and Systems, pp. 1896-1901.

[3] Aggarwal, J. and Cai, Q. (1999): "Human Motion Analysis: A Review", Computer Vision and Image Understanding, Vol. 73, pp. 428-440.

[4] Do, J.-H. and Bien, Z. (2007): "Three-stage Model for Robust Real-time Face Tracking," Int. J. Imaging System Technology, Vol. 17, pp. 321-327.

[5] Barrera, P., Canas, J.M. and Matellan, V. (2005): "Visual Object Tracking in 3D with Color Based Particle Filter," Proc. of World Academy of Science, Engineering and Tech., vol. 4, pp. 200-203.

[6] Isard, M. and Blake, A. (1998): "CONDENSATION – Conditional Density Propagation for Visual Tracking," Int. Journal of Computer Vision, Vol. 20, No. 1, pp. 5-28.

[7] Perez, P., Vermaak, J. and Blake, A. (2004): "Data Fusion for Visual Tracking with Particles," Proc. of IEEE, Vol. 92, No. 3, pp. 495-513.

[8] Yin, Z. and Collins, R. (2006): "Spatial Divide and Conquer with Motion Cues for Tracking through Clutter," IEEE Conf. on CVPR, pp. 570-577.

[9] Wu, Y. and Yu, T. (2006): "A Field Model for Human Detection and Tracking", IEEE Trans. on PAMI, Vol. 28, No. 5, pp.753-765.

[10] Viola, P. and Jones, M. (2001): "Rapid Object Detection Using a Boosted Cascade of Simple Features," IEEE Conf. on CVPR, pp. 511-518.

[11] Huang, Y. and Essa, I. (2005): "Tracking Multiple Objects through Occlusions," IEEE Conf. on CVPR, Vol. 2, pp. 1051-1058.

[12] Okuma, K., Taleghani, A., Freitas, N., Little, J. and Lowe, D. (2004): "A Boosted Particle Filter: Multitarget Detection and Tracking," European Conf. on Computer Vision, pp. 28-39.

[13] Khan, Z., Balch, T. and Dellaert, F. (2005): "MCMC-based Particle Filtering for Tracking a Variable Number of Interacting Targets," IEEE Trans. on PAMI, Vol. 27, No. 11, pp. 1805-1819.

[14] Li, J. and Chua, C. (2003): "Transductive Inference for Color-Based Particle Filter Tracking," Int. Conf. on Image Processing, Vol. 3, pp. 949-952.
[15] Nummiaro, A., Koller-Meier, E. and Gool, L. (2002): "A Color-based Particle Filter," Int. Workshop on Generative-Model-Based Vision, pp. 53-60.
[16] Bagnato, L., Sorci, M., Antonini, G., Baruffa, G., Maier, A., Leathwood, P. and Thiran, J. (2007): "Robust Infants Face Tracking Using Active Appearance Models: a Mixed-State CONDENSATION Approach," Int. Symposium on Visual Computing, Vol. I, pp. 13-23.
[17] Yoon, S. and Lee, S. (2004): "Face Tracking Using Particle Filter in the Complex Background," Int. Conf. on Artificial Reality and Telexistence, 4 pages.
[18] Martinez-del-Rincon, J., Orrite-Urunuela, C. and Herrero-Jaraba, J. (2007): "An Efficient Particle Filter for Color-Based Tracking in Complex Scenes," IEEE Int. Conf. on Advanced Video and Signal based Surveillance (AVSS), pp. 176-181.
[19] Tracking with non-linear dynamic models, Chpt. 2, http://courses.csail.mit.edu/6.869/handouts/particles.pdf
[20] Nummiaro, A., Koller-Meier, E. and Gool, L. (2002): "An Adaptive Color-based Particle Filter," Image Vision Computing, Vol. 21, No. 1, pp. 99-110.
[21] Comaniciu, D., Ramesh, V. and Meer, P. (2000): "Real-time Tracking of Non-Rigid Objects Using Mean Shift," IEEE Conf. on CVPR, pp. 142-149.
[22] Perez, P., Hue, C., Vermaak, J. and Gangnet, M. (2002): "Color-based Probabilistic Tracking," European Conf. on Computer Vision, pp. 661-675.
[23] Viola, P. and Jones, M. (2001): "Robust Real-time Object Detection", Int. Workshop on Statistical Learning and Computational Theories of Vision – Modeling, Learning, Computing, and Sampling, pages 25.
[24] Meynet, J. (2003): "Fast Face Detection Using AdaBoost", pages 96.
[25] Triesch, J. and Malsburg, C. (2001): "Democratic Integration: Self-Organized Integration of Adaptive Cues," Neural Computation, Vol. 13, pp. 2049-2074.
[26] Comaniciu, D., Ramesh, V. and Meer, P. (2003): "Kernel-based Object Tracking," IEEE Trans. on PAMI, Vol. 25, No. 5, pp. 564-577.
[27] Wu, Y. and Huang, T. S. (2004): "Robust Visual Tracking by Integrating Multiple Cues Based on Co-Inference Learning," Int. J. Computer Vision, Vol. 58, No. 1, pp. 55-71.

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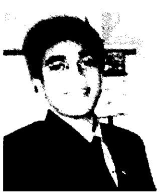

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