Independent Component Analysis-Based Background Subtraction for Indoor Surveillance

Du-Ming Tsai and Shia-Chih Lai

Abstract—In video surveillance, detection of moving objects from an image sequence is very important for target tracking, activity recognition, and behavior understanding. Background subtraction is a very popular approach for foreground segmentation in a still scene image. In order to compensate for illumination changes, a background model updating process is generally adopted, and leads to extra computation time. In this paper, we propose a fast background subtraction scheme using independent component analysis (ICA) and, particularly, aims at indoor surveillance for possible applications in home-care and health-care monitoring, where moving and motionless persons must be reliably detected. The proposed method is as computationally fast as the simple image difference method, and yet is highly tolerant to changes in room lighting. The proposed background subtraction scheme involves two stages, one for training and the other for detection. In the training stage, an ICA model that directly measures the statistical independency based on the estimations of joint and marginal probability density functions from relative frequency distributions is first proposed. The proposed ICA model can well separate two highly-correlated images. In the detection stage, the trained de-mixing vector is used to separate the foreground in a scene image with respect to the reference background image. Two sets of indoor examples that involve switching on/off room lights and opening/closing a door are demonstrated in the experiments. The performance of the proposed ICA model for background subtraction is also compared with that of the well-known FastICA algorithm.

Index Terms—Background subtraction, foreground segmentation, independent component analysis (ICA), indoor surveillance.

I. INTRODUCTION

In video surveillance, detection of moving objects from an image sequence is very important for the success of object tracking, activity recognition, and behavior understanding. Motion detection aims at segmenting foreground regions corresponding to moving objects from the background. Background subtraction and temporal differencing are two popular approaches to segment moving objects in an image sequence under a stationary camera. Background subtraction detects moving objects in an image by evaluating the difference of pixel features of the current scene image against the reference background image. This approach is very sensitive to illumination changes without adaptively updating the reference background. Temporal differencing calculates the difference of pixel features between consecutive scene frames in an image sequence. It is very effective to accommodate environmental changes, but generally can only recover partial edge shapes of moving objects. In this study, we propose a fast background subtraction scheme using independent component analysis (ICA) and, particularly, aim at indoor surveillance for possible home-care and health-care applications.

Hu et al. [1] categorized motion segmentation approaches as background subtraction, temporal differencing, and optical flow. As aforementioned, background subtraction and temporal differencing are applied to stationary cameras. Optical flow methods can be used for nonstationary cameras, which assign to every pixel a 2-D velocity vector over a sequence of images. Moving objects are then detected based on the characteristics of the velocity vectors. Optical flow methods are computationally intensive, and can only detect partial edge shapes of moving objects.

In order to make the background subtraction adaptive to environmental changes such as illumination variations, many background model updating strategies were proposed. Wren et al. [2] developed a system called Pfinder for person segmentation, tracking and interpretation. They modeled each pixel of the background over time with a single Gaussian distribution. Since the estimation of Gaussian parameter values using the standard algorithms such as Expectation Maximization (EM) for each pixel in an image is computationally prohibited, recursive updating using a simple linear adaptive filter is applied for real-time implementation. The general form of the recursive linear filter formulation can be given by [3]

$$\theta_t = \eta_t \cdot \nabla(x_i; \theta_{t-1}) + (1 - \eta_t) \cdot \theta_{t-1}$$  \hspace{1cm} (1)$$

where the model parameter $\theta_t$ at time $t$ is updated by a local estimate $\nabla(x_i; \theta_{t-1})$ with a learning rate $\eta_t$. The learning rate used in the linear filter is usually fixed throughout the whole sequence of images and obtained by try-and-error. It controls the speed at which the model adapts to changes. A small value of learning rate results in slow convergence when a Gaussian adapts to background changes. Conversely, a large value of learning rate may improve the convergence speed, but the new background model will not maintain sufficient historical information of previous images. The single Gaussian updating models were also adopted in the [4]–[7] for background subtraction.

A robust background modeling is to represent each pixel of the background image over time by a mixture of Gaussians. This approach was first proposed by Stauffer and Grimson [8], [9], and became a standard background updating procedure for comparison. In their background model, the distribution of

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The authors are with the Department of Industrial Engineering and Management, Yuan-Ze University, Chung-Li 32003, Taiwan, R.O.C. (e-mail: iedmntsai@saturn.yzu.edu.tw; summer.lai@delta.com.tw).

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recently observed value of each pixel in the scene is characterized by a mixture of several Gaussians. All parameter values of the Gaussian mixture model are updated according to (1) using a fixed learning rate (i.e., \( \eta = \alpha \)). The background model can deal with multimodal distributions caused by shadows, swaying branches, etc. It can handle slow lighting changes by slowly adapting the parameter values of the Gaussians. KaewTraKulPong and Bowden [10] and Lee [11] further presented effective background updating schemes to improve the convergence rate of Gaussian mixture models. Li et al. [12] derived a theoretical analysis for the choice of the fixed learning rate \( \alpha \).

Instead of modeling the feature vectors of each pixel by a mixture of several Gaussians, Elgammal et al. [13] proposed to evaluate the probability of a background pixel using a nonparametric kernel density estimation based on very recent historical samples in the image sequence. In order to achieve quick adaptation to changes in the scene for sensitive detection and low false positive rates, they proposed a way to combine the results of short-term and long-term background models for better update decision. Kernel density estimation is very computationally intensive. Elgammal et al. [14] further proposed a fast nonparametric kernel density estimation algorithm for object tracking. By considering a Gaussian kernel function, the Fast Gauss Transform [15], [16] improves the computation of the kernel density estimation from \( O(N^2) \) to \( O(N) \), where \( N \) is the number of samples used in the kernel model. Ianasi et al. [17] also used nonparametric kernel density estimation for moving object detection and tracking. They proposed a fast algorithm using multiresolution and recursive density estimation with mean shift based mode tracking.

The background subtraction methods reviewed above have worked successfully for indoor and outdoor surveillances, where the environment may change gradually or abruptly over time. Although many relatively fast background modeling methods have been proposed for real-time implementation, the updating process still consumes a significant amount of total computation time, and restricts the image frame to a small size (e.g., 150 × 200). This causes a low image resolution, and the object of interest may appear as a tiny foreground region in the scene image. Besides the extra computational time of background updating, one of the limitations of the adaptive background modeling is that it can wrongly absorb a foreground object into the background if the object remains motionless for a long period of time. For home-care surveillance, a foreground person may watch TV or fall asleep in the living room and remains still for long time duration. Or, for health-care monitoring, a patient may fall off the bed and become unconscious. The foreground objects in such circumstances can not be detected with the newly updated background model. To cope with the problem of motionless foreground objects, a reference background image that contains no moving objects may be required. Background subtraction based on a single reference image is very computationally fast. However, it is also very sensitive to illumination changes, which deter the use of such an approach in many surveillance applications.

In this paper, we propose a simple and fast background subtraction scheme without background model updating, and yet it is tolerable to changes in room lighting for indoor surveillance using Independent Component Analysis (ICA). ICA is a novel statistical signal process technique to extract independent sources given only observed data that are mixtures of unknown sources without any prior knowledge of the mixing mechanisms [18], [19]. In the ICA model, the observed signals are generally assumed to be a linear mixture of the unknown sources from a mixing matrix. The estimated source signals are termed independent components (ICs), and the inverse of the mixing matrix is called de-mixing matrix. The de-mixing matrix is solved by maximizing the independency of the estimated source signals.

In this study, we use ICA to detect foreground objects in a sequence of images. Since the moving objects and the stationary background in an image are considered to be independent, ICA is applied to obtain the de-mixing matrix that can separate a scene image into foreground objects and still background. The proposed ICA-based background subtraction scheme involves two processing stages: training stage and detection stage. In the training stage, two sample images, one representing the reference background and the other containing arbitrary foreground objects, are selected to form the data matrix of the ICA model. Then, an ICA algorithm is applied to solve for the de-mixing matrix. In the detection stage, the reference background image used in training and the current scene image in the sequence are used to form the data matrix. One of the two vectors of the trained de-mixing matrix is associated with foreground objects, and is employed as a filter to extract the foreground objects in the scene image. Since the row vector of the de-mixing matrix is only of a small size of \( 1 \times 2 \), it is very computationally efficient in the detection stage. It then allows high frame rates for large image sizes, or leaves sufficient time for high-level processes such as tracking and activity recognition.

The two sample images that form the data matrix in the training stage basically are identical except for the relatively small foreground region in the whole image. Therefore, these two signals show a high correlation coefficient. The well-known FastICA algorithm [20] cannot effectively recover highly-correlated source signals. In this study, an independent component analysis model that directly measures the difference of the joint probability density function (PDF) and the product of marginal probability density functions is proposed. The PDFs are estimated from the relative frequency distributions, and the Particle Swarm Optimization (PSO) algorithm is used to search for the best de-mixing matrix of the ICA model. The proposed ICA model can well separate highly correlated data, and the estimated de-mixing matrix can effectively segment foreground objects under illumination changes for indoor surveillance applications.

The organization of this paper is as follows. Section II first overviews the ICA model. The proposed ICA model that directly measures the difference between the joint PDF and the product of marginal PDFs is then discussed. The PSO search algorithm that determines the best de-mixing matrix from the proposed ICA model is finally presented. Section III describes two sets of experiments used to demonstrate the efficiency and effectiveness of the proposed method, and to compare the detection performance with the FastICA algorithm and the image difference method. The paper is concluded in Section IV.
II. ICA-BASED BACKGROUND SUBTRACTION

A. Basic ICA Model

In the basic ICA model [19], [20], the observed mixture signals $\mathbf{X}$ can be expressed as

$$ \mathbf{X} = \mathbf{A} \mathbf{S} $$

where $\mathbf{A}$ is an unknown mixing matrix, and $\mathbf{S}$ represents the latent source signals, meaning that they cannot be directly observed from the mixture signals $\mathbf{X}$. The ICA model describes how the observed mixture signals $\mathbf{X}$ are generated by a process that uses the mixing matrix $\mathbf{A}$ to mix the latent source signals $\mathbf{S}$. The source signals are assumed to be mutually statistically independent. Based on the assumption, the ICA solution is obtained in an unsupervised learning process that finds a de-mixing matrix $\mathbf{W}$. The matrix $\mathbf{W}$ is used to transform the observed mixture signals $\mathbf{X}$ to yield the independent signals, i.e., $\mathbf{W} \mathbf{X} = \mathbf{Y}$. The independent signals $\mathbf{Y}$ are used as the estimates of the latent source signals $\mathbf{S}$. The components of $\mathbf{Y}$, called independent components, are required to be as mutually independent as possible.

The objective of the algorithm for an ICA model is to maximize the statistical independency (non-Gaussianity) of the ICs. The non-Gaussianity of the ICs can be measured by the negentropy $J(\mathbf{y}) = H(\mathbf{y}_{\text{gauss}}) - H(\mathbf{y})$, which is given by

$$ J(\mathbf{y}) = \{E[G(y)] - E[G(y)]\}^2 $$

where $\mathbf{y}_{\text{gauss}}$ is a Gaussian random vector of the same covariance matrix as $\mathbf{y}$. $H$ is the entropy of a random vector $\mathbf{y}$.

The negentropy is always non-negative and is zero if and only if $\mathbf{y}$ has a Gaussian distribution. It is well justified as an estimator of the non-Gaussianity of the ICs. Since the problem in using negentropy is computationally very difficult, an approximation of negentropy is proposed as follows:

$$ J(\mathbf{y}) \approx \{E[G(y)] - E[G(y)]\}^2 $$

where $y$ is a Gaussian variable of zero mean and unit variance. $G$ is a nonquadratic function, which is generally given by $G(y) = -\exp(-y^2/2)$ or $G(y) = -(1/(a_1)) \log \cosh(a_1 y)$ with $1 \leq a_1 \leq 2$. The FastICA algorithm [21], [22] has been one of the most popular optimization methods in ICA, which is based on a fixed-point iteration scheme for finding a maximum of the negentropy.

B. Proposed ICA Model

In order to separate foreground objects from the background in a scene image, we need at least two sample images to construct the mixture signals in the ICA model. Let the sample images be of size $m \times n$. Each sample image is organized as a row vector of $K$ dimensions, where $K = m \times n$. Denote by $\mathbf{x}_b = [x_{b1}, x_{b2}, \ldots, x_{bK}]$ the reference background image containing no foreground objects, and $\mathbf{x}_f = [x_{f1}, x_{f2}, \ldots, x_{fK}]$ the foreground image containing an arbitrary foreground object in the stationary background. In the training stage of the proposed background subtraction scheme, the ICA model is given by

$$ \mathbf{Y} = \mathbf{W} \cdot \mathbf{X}_T $$

where

$$ \mathbf{X}_T = [\mathbf{x}_b, \mathbf{x}_f]^T $$

is the mixture data matrix of size $2 \times K$;

$$ \mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2]^T $$

is the de-mixing matrix, in which

$$ \mathbf{w}_i = [w_{i1}, w_{i2}], i = 1, 2; $$

$$ \mathbf{Y} = [y_{11}, y_{12}]^T $$

is the estimated source signals, in which

$$ y_{ij} = [y_{i1}, y_{i2}, \ldots, y_{iK}], i = 1, 2. $$

ICA aims to find a $2 \times 2$ de-mixing matrix $\mathbf{W}$ of the data matrix $\mathbf{X}_T$ such that one of the two row vectors in the estimated source signals $\mathbf{Y}$ will contain only the foreground object in a uniform region without the detailed contents of the background. The $1 \times 2$ row vector $\mathbf{w}_i$ associated with the source signal of the foreground object in the de-mixing matrix $\mathbf{W}$ is then used in the detection stage to separate foreground objects in each scene image of the video sequence.

The two sample images $\mathbf{x}_b$ and $\mathbf{x}_f$ in the mixture data matrix $\mathbf{X}_T$ can be highly correlated since both contain a large portion of the same stationary background region. The conventional FastICA algorithm cannot effectively separate source signals which are correlated in nature. In this study, the statistical independence is directly employed to form the objective of the ICA model, i.e., if two random variables $y_{1k}$ and $y_{2k}$ are mutually independent, the joint PDF $p(y_{1k}, y_{2k})$ can be factorized as

$$ p(y_{1k}, y_{2k}) = p_1(y_{1k}) \cdot p_2(y_{2k}) $$

where $p_i(y_{ik})$ is the marginal PDF of source signal $y_{ik}, i = 1, 2$, and $k = 1, 2, \ldots, K$. Therefore, the objective of the proposed ICA model for background subtraction is to minimize the absolute difference between the joint PDF and the product of marginal PDFs. That is

$$ \min_{\mathbf{W}} \sum_{k=1}^{K} |p(y_{1k}, y_{2k}) - p_1(y_{1k}) \cdot p_2(y_{2k})|. \tag{4} $$

The difficulty of applying the definition of statistical independence in (4) is that we have no prior knowledge on the joint and marginal PDFs. Since the ICA model applied to background subtraction in this study involves only two source signals of foreground and background, the combination of $(y_{1k}, y_{2k})$ falls within a manageable number. The joint and marginal PDFs are simply estimated from the relative frequency of the discrete observed data. We start with the construction of a histogram for each individual source signal (i.e., marginal PDF). The range of signal values covered by the data is initially broken up into $N$ disjoint adjacent intervals, each of the same width. The Sturges’s rule [23] is used as a guideline for choosing the initial number of intervals.

Given $N$ intervals in each of the two marginal density distributions, the number of 2-D grids in the joint density distribution becomes a large amount of $N^2$. When most of the grids have zero-entries in the joint density distribution, the estimation of the joint PDF becomes very unstable and leads to false
separation of source signals. In order to prevent zero probabilities in most of the grids in the joint PDF, the interval with zero entries in the marginal density distribution is merged with its neighboring intervals. The interval merging process is repeated until all resulting intervals of each marginal density distribution have sufficient entries. In this study, we use 20 entries as the threshold. By the end of the merge, each interval in individual marginal density distributions may have different widths. The resulting interval widths used for estimating marginal PDFs are also used to estimate the joint PDF.

Let \( c_{i,k} \) be the \( k \)-th interval of source signal \( y_i \), \( i = 1, 2 \) and \( k = 1, 2, \ldots, n_i \), where \( n_i \) is the resulting number of intervals for source signal \( y_i \). Also let \( h(c_{i,k}) \) be the resulting number of entries in the interval \( c_{i,k} \). The marginal PDF of source signal \( y_i \) at interval \( c_{i,k} \) is estimated by

\[
\hat{p}_i(c_{i,k}) = \frac{h(c_{i,k})}{K}, \quad i = 1, 2; \quad k = 1, 2, \ldots, n_i.
\]

The joint PDF of \( y_1 \) and \( y_2 \) at grid \( (c_{1,k_1}, c_{2,k_2}) \) is estimated by

\[
\hat{p}(c_{1,k_1}, c_{2,k_2}) = \frac{h(c_{1,k_1}, c_{2,k_2})}{K}
\]

where \( h(c_{1,k_1}, c_{2,k_2}) \) is the number of entries falling in the 2-D grid \( (c_{1,k_1}, c_{2,k_2}) \); \( c_{i,k} \) is the \( k \)-th merged interval of source signal \( y_i \), \( k = 1, 2, \ldots, n_i \) for \( i = 1, 2 \).

For a given de-mixing matrix \( W \), the source signals \( y_1 \) and \( y_2 \) are estimated by

\[
Y = [y_1, y_2]^T = WX_T
\]

and their joint and marginal PDFs can be estimated accordingly from the relative frequency distributions. The objective of the proposed ICA model is, therefore, reformulated as

\[
G(W \cdot X_T) = \sum_{k_1=1}^{n_1} \sum_{k_2=1}^{n_2} [\hat{p}(c_{1,k_1}, c_{2,k_2}) - \hat{p}_1(c_{1,k_1}) \cdot \hat{p}_2(c_{2,k_2})]. \quad (5)
\]

The objective function of the ICA model defined in (5) is not differentiable. In this study, we, therefore, propose a stochastic optimization procedure based on the particle swarm optimization (PSO) algorithm to determine the de-mixing matrix \( W \) that minimizes the objective \( G(W \cdot X_T) \).

**C. PSO Procedure**

Particle swarm optimization is an evolutionary computation technique originally developed by Kennedy and Eberhart [24]. PSO resembles the social interaction from a school of flying birds. Individuals in a group of flying birds are evolved by cooperation and competition among the individuals themselves through generations [25]. Each individual, named as a “particle”, adjusts its flying according to its own flying experience and its companions’ flying experience. Each particle with its current position represents a potential solution to the problem in hand. In this study, each particle is treated as a point in a 4-D space since the de-mixing matrix \( W \) is of size \( 2 \times 2 \).

In PSO, a number of particles, which simulate a group of flying birds, are simultaneously used to find the best fitness in the search space. At each iteration, every particle keeps track of its personal best position by dynamically adjusting its flying velocity. The new velocity is evaluated by its current velocity and the distances of its current position with respect to its previous best local position and the global best position. After a sufficient number of iterations, the particles will eventually cluster around the neighborhood of the fittest solution.

Let the \( t \)-th particle be represented as \( W_t = [(w_{t11}, w_{t12}), (w_{t21}, w_{t22})]^T \). The best previous position, i.e., the position giving the best fitness value, of particle \( t \) is recorded and represented as \( W_t = [(b_{t11}, b_{t12}), (b_{t21}, b_{t22})]^T \). Assume there are a total of \( P \) particles in the PSO. Let \( B^g = [(b_{11}^g, b_{12}^g), (b_{21}^g, b_{22}^g)]^T \) denote by the best particle that gives the current optimal fitness value among all the particles in the population. The rate of the position change, i.e., the velocity, for particle \( t \) is represented by \( V_t = [(v_{t1}, v_{t12}), (v_{t21}, v_{t22})]^T \). Each particle moves over the search space with a velocity dynamically adjusted according to its historical behavior and its companions. The velocity and position of a particle are updated according to the following equations [24]:

\[
\begin{align*}
\dot{w}_{trc}^k &= w_{trc}^k + d_1 \cdot \text{RND}_1 \cdot (b_{trc}^k - w_{trc}^k) \\
&\quad + d_2 \cdot \text{RND}_2 \cdot (b_{trc}^k - u_{trc}^k) \quad (6a) \\
w_{trc}^k &= w_{trc}^k + w_{trc}^k \quad \text{for} \quad t = 1, 2, \ldots, P, \quad r = 1, 2 \quad \text{and} \quad c = 1, 2
\end{align*}
\]

where \( \text{RND}_1 \) and \( \text{RND}_2 \) are two random numbers in the range between 0 and 1; \( d_1 \) and \( d_2 \) are two positive constants.

The two positive constants \( d_1 \) and \( d_2 \) are the weights used to regulate the acceleration of self-cognition (a local best) and social interaction (a global best). Kennedy and Eberhart [24], and Shi and Eberhart [25] suggested \( d_1 = d_2 = 2 \) since they make the weights for “cognition” and “social” parts to be 1 on average. They are also the values adopted in this study. The velocity equation in (6a) calculates the particle’s new velocity in each dimension according to its previous velocity and the distances of its current position from its own best experience (i.e., position) and the group’s best experience. Then the particle moves toward a new position according to the position update equation in (6b). The performance of each particle is measured by the fitness value, i.e., the objective function value in (5). When all particles are evaluated, the global best position is updated by

\[
B^g = \arg \min_{B_t} (G(B_t \cdot X_T)).
\]

The procedure is repeated for a sufficient number of iterations, and the final global best position \( B^g \) is used as the de-mixing matrix \( W \), which will be used in the detection stage for separating foreground objects from the background.

Experiments have shown that the PSO search process converges fast after 150 iterations for a set of numerous test samples evaluated in this study. Therefore, 200 iterations are considered to be sufficient for our problem. Given the objective of minimizing the difference between the joint PDF and the product of marginal PDFs, the PSO algorithm with a moderate number of iterations can search for an intermediate de-mixing matrix that reduces the fitness value, but not a de-mixing matrix that results in a zero fitness value, i.e., two completely independent
source signals. Therefore, the proposed ICA model with the PSO search procedure can recover two highly correlated source signals. The fixed-point algorithm for the negentropy model is converged fast and finds straightly a de-mixing matrix that separates two mixture signals into two independent signals, even though they are highly correlated in nature. Note that when the proposed ICA model is solved by the PSO algorithm with an extremely large number of iterations (e.g., 5000 or more), the estimated source signals are then similar to those of the FastICA algorithm.

D. Foreground Detection

To demonstrate the proposed ICA model for background subtraction, Fig. 1(a) and (b) presents a reference background image $x_b$ and a scene image $x_f$ containing a foreground object, respectively. The correlation coefficient between the two images is 0.90. Let $f(i,j)$ be the 2-D image of size $m \times n$. It is first reshaped as a vector $x$ by the following transformation:

\[
x = \{x((i-1) \cdot n + j) = f(i,j) \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\}.
\]

The de-mixing matrix obtained from the PSO search of the proposed ICA model is given by $W = [w_1, w_2]^T = [(0.8940, 0.4480), (-0.6625, 0.7490)]^T$. Therefore, the source signals can be estimated by

\[
Y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = W \cdot X = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \cdot \begin{bmatrix} x_b \\ x_f \end{bmatrix}.
\]

The resulting source signal $y_i = \{y_{i,j}\}; i = 1, 2$ and $j = 1, 2, \ldots, m \cdot n$, in vector form is converted back to a 2-D image by

\[
I_i(u,v) = y_{i,(u-1)n+v} \text{ for } u = 1, 2, \ldots, m \text{ and } v = 1, 2, \ldots, n.
\]

In order to visualize the resulting value of $I_i(u,v)$ in a gray-level image, $I_i(u,v)$ is transformed by

\[
I'_i(u,v) = I_i(u,v) \cdot c \cdot \sigma_i + \mu_i
\]

where $\mu_i$ and $\sigma_i$ are the mean gray value and standard deviation of the reference background image $x_b = \{x_{bj}\}; j = 1, 2, \ldots, m \cdot n$; $c$ is a conversion constant that sets up the range of the converted gray values; it is given by $c = 0.5$ in this study.

To segment foreground objects in the estimated source image $I'_i(u,v)$ for some $i = 1$ or 2, an adaptive threshold is used to binarize the image. The threshold for segmentation in image $I'_i(u,v)$ is given by a simple statistical control limit

\[
\mu_i + l \cdot \sigma_i
\]

where $\mu_i$ and $\sigma_i$ are the mean and standard deviation of image $I'_i(u,v)$, and $l$ is the control constant, which is given by 1.5 in this study. If

\[
I'_i(u,v) < \mu_i + l \cdot \sigma_i
\]

then pixel $(u,v)$ is a background point and shown in white in the binary image. Otherwise, it is classified as a foreground point and shown in black in the segmented image. Fig. 1(c) and (d) depicts the estimated source images $I'_i(u,v)$, $i = 1, 2$, which are respectively derived from the de-mixing vectors $w_1 = [0.8940, 0.4480]$ and $w_2 = [-0.6625, 0.7490]$. It is apparent from the separation results that de-mixing vector $w_1$ corresponds to the foreground object, and vector $w_2$ is associated with the reference background. The estimated source image $I_1(u,v)$ in Fig. 1(d) clearly shows the foreground object without the details of the reference image. The foreground object can, therefore, be segmented easily in the estimated source image with simple thresholding, as seen in Fig. 1(e).

The de-mixing vector corresponding to foreground objects is then used in the detection stage to separate foreground objects in each scene image of a video sequence. The resulting de-mixing vector used for foreground segmentation must have the two elements with opposite signs. The de-mixing vector associated with the reference background is discarded for further consideration in the detection stage.

In the detection stage, the reference background image $x_b$ is retained. A scene image $x_t$ at time frame $t$ in a video sequence along with the background image $x_b$ are used to construct the data matrix $X_t = [x_b, x_t]^T$. Then $w = [w_1, w_2]$ be the de-mixing vector corresponding to foreground objects in the training stage. Then the sole estimated source image $y_t$ is given by

\[
y_t = wX_t = [w_1, w_2] \begin{bmatrix} x_b \\ x_t \end{bmatrix}.
\]

Once the source image $y_t$ is obtained, it can be converted to a gray-level image using (7) for visual display, and thresholded to a binary image using (8). The de-mixing vector $w$ is obtained from the training stage, and the ICA modeling and optimization are not required in the detection stage. It is, therefore, very computationally fast to derive the estimated source image, and to detect foreground objects with or without motions in the scene image.

The 2-D de-mixing vector $w = [w_1, w_2]$ with opposite signs of elements, i.e., $w_1 \cdot w_2 < 0$, can be treated as a convolution filter for image difference. It assigns weight $w_1$ to the 2-D reference background image $f_b(x,y)$, and weight $w_2$ to the
2-D scene image \( f(x, y) \). The response amplitude indicates the presence/absence of foreground objects in the scene. If the magnitude of the weighted difference \( |w_1 \cdot f_b(x, y) + w_2 \cdot f_t(x, y)| \) is distinctly large, then it shows the strong evidence that \((x, y)\) is a foreground point.

III. EXPERIMENTAL RESULTS

This section presents the experimental results from two sets of indoor image sequences to evaluate the performance of the proposed ICA-based background subtraction method. The test images in the experiments were 150 × 200 pixels wide with 8-bit gray levels. In the PSO search algorithm, the required parameters were set up as follows: the number of particles was 20, the weights \( d_1 = d_2 = 2 \), and the maximum number of iterations was 200. In the detection stage, the constant \( c \) in (7) for converting ICA signal values to gray values was set at 0.5, and the control constant \( l \) in (8) for binary thresholding was given by 1.5 for all scene images. The implementation of the proposed method runs at a very fast speed of 142 fps (frames per second) for 150 × 200 gray-level images on a personal computer with an AMD 64-bit 1.8-GHz processor. In the experiments, we also compare the performance of the proposed method with the FastICA algorithm, and the simple image difference method. For a fair comparison, the same parameter values of \( c \) and \( l \) in (7) and (8) were applied for the FastICA and image difference methods, as well. To show the primary performance of the proposed method, postprocessing such as noise cleaning and connected component analysis were not introduced to the segmented images.

A. Single Reference Background

The first test sample is a scene room with a large window. The room has three sets of fluorescent lights on the ceiling. It is not uncommon that a room will have all lights on, all lights off, or partial lights in daily life. The illumination in the room is, therefore, affected by indoor lights and outdoor sunlight through the window, and the illumination could be changed gradually or suddenly. Fig. 2(a) and (b) shows, respectively, a reference background image of the room \( x_b \), and a scene image containing a walking person \( x_f \), where all three sets of fluorescent lights were turned on. Note that the window region is brighter than the remaining area in the image. Fig. 2(c) and (d) shows the estimated source images from the respective de-mixing vector \( w_1 = [0.7996, 0.6006] \) and \( w_2 = [0.7641, -0.6452] \). It is visibly shown in Fig. 2(d) that \( w_2 \) corresponds to the foreground, which distinctly preserves the foreground object without the detailed contents of the reference background.

In the detection stage of the first test sample, the example came from a scenario that a person walked in the room, in which all three sets of lights were originally turned on, then one set of the ceiling lights was switched off for a period of time, and finally two sets of lights were turned off. The gray-level images shown in the first column (a) of Fig. 3 display the original sequence at varying frames. The video images were taken at 5 fps. The symbol \( f \) marked in the figure represents the frame number in the image sequence.

Prior to frame 25 (\( f = 25 \)), all three sets of lights were turned on. Images between frames 65 and 88 were the results of switching off one set of lights. After frame 153, two sets of lights were turned off. Note that the two images at frames 65 and 153 do not present any foreground objects, and they were taken under dramatic changes in scene lighting. The second and third columns (b) and (c) of Fig. 3 are the separation results, shown

Fig. 2. Experimental results on a room with a large window (training stage): (a) reference background image; (b) scene image containing a person whose clothes have similar intensities to the background wall; (c) separated background image from \( w_1 = [0.7996, 0.6006] \); (d) separated foreground image from \( w_2 = [0.7641, -0.6452] \).

Fig. 3. Experimental results on a room with a large window (detection stage): The left-most column (a) shows the discrete scene images in a video sequence taken at 5 fps. The symbol \( f \) indicates the frame number in the sequence. Columns 2, 3, and 4 (b)–(d) give the detected foregrounds from the proposed method, FastICA, and the image difference method, respectively.
as gray-level images using (7), from the proposed method and the FastICA algorithm, respectively. The fourth column (d) of Fig. 3 is the difference values, also shown as gray-level images using (7), from the simple image difference method.

Given the training sample images in Fig. 2(a) and (b), the FastICA algorithm generates a de-mixing vector of \([3.3096, -3.2558]\), which is very close to the simple image difference method that uses \([1, -1]\) as the filter. From the second column (b) of Fig. 3, it is apparent that the proposed method can distinctly enhance the walking person and remove the background details in the separated images, even with large changes in illumination. The FastICA algorithm and the image difference method only work well under fixed lighting. When the room lighting is distinctly different from the one in the reference background image, both the moving person and the background details are presented in the resulting images, as seen in the third and fourth columns of Fig. 3.

Fig. 4 shows the binarization results from the images in Fig. 3. The first column of Fig. 3 is repeated in the first column (a) of Fig. 4 for visual evaluation of the segmentation results. The second, third, and fourth columns (b)–(d) of Fig. 4 are the thresholding results from the proposed method, the FastICA algorithm, and the image difference method, respectively. It can be observed from the binary images that the FastICA and the image difference methods detect the bright window as a foreground object, and the moving person cannot be identified as a foreground object when she passed through the window. The proposed method can effectively detect the walking person even under distinct changes in room lighting.

**B. Multiple Reference Backgrounds**

In indoor surveillance, it is quite common to have a door widely open, completely closed, or left half open in a scene room. Or, a person may be opening or closing a door when he/she walks into or out of the room. One may encounter the same situation when opening or closing a curtain across the window. A door or a curtain is a nonstationary background object, and should not be identified as a foreground object in background subtraction. The problem of such nonstationary background objects can be coped with multiple reference backgrounds. The second indoor surveillance test sample involves a scene room with opening and closing of a door. To apply the proposed method for background subtraction, we first select two reference background scenes \(x_{t1}\) and \(x_{t2}\), one having the door widely open and the other having the door fully closed. We then individually train two ICA models using the two reference background images, and obtain two de-mixing vectors \(w_{f1}\) and \(w_{f2}\) that can be used to separate foreground objects in the image. In the detection stage, a scene image \(x_t\) in the video sequence is individually convoluted with \(w_{f1}\) and \(w_{f2}\) by

\[
y_{f1} = w_{f1} \cdot \begin{bmatrix} x_{t1} \\ x_t \end{bmatrix}, \quad \text{and} \quad y_{f2} = w_{f2} \cdot \begin{bmatrix} x_{t2} \\ x_t \end{bmatrix}.
\]

Let \(E_{f1}\) and \(E_{f2}\) be the respective binary images of \(y_{f1}\) and \(y_{f2}\), where a foreground pixel and a background pixel are, respectively, given by the values of 1 and 0. Given a scene image containing a half-open door, or an opening/closing operation of the door, we expect that the pixels of the nonstationary door will fall within either the reference background with a widely open door, or the one with a fully closed door. A true foreground pixel should be present in both binary images \(E_{f1}\) and \(E_{f2}\), i.e.,

\[
S_{f1,f2} = E_{f1} \cap E_{f2}.
\]

Fig. 5 show two sets of mixture data used for training the ICA models. The first set in Fig. 5(a1) and (b1) involves the background scene \(x_{b1}\) with the door completely closed, and the second set in Fig. 5(c1) and (d1) contains the background scene \(x_{b2}\) with the door widely open. Fig. 6(a1)–(c1) shows three scene images for foreground segmentation, in which (a1) contains a person walking through a widely open door, (b1) involves a man passing through a half-open door, and (c1) is the background scene with a half-open door. Fig. 6(a2)–(c2) gives the binary results \(E_{f1}\) from the first reference background \(x_{b1}\), and Fig. 6(a3)–(c3) shows the binary results \(E_{f2}\) from the second reference background \(x_{b2}\). Fig. 6(a4)–(c4) shows the intersection results of \(E_{f1}\) and \(E_{f2}\). It can be observed from Fig. 6 that
the foreground object can be reliably segmented without presenting the nonstationary door as a foreground region.

C. Effect of Varying Foreground Objects

In this subsection, we evaluate the effect of object sizes and intensity contrast for foreground segmentation. Fig. 7(a) and (b) shows the reference background and the foreground image used in the training process. The foreground image contains a tiny girl wearing white clothes similar to the background. The resulting de-mixing vector is \[ w = [0.7327, -0.6486] \]. Fig. 7(c)–(e) displays the detection results of the same girl walking toward the still camera. The object sizes in the scene images have been distinctly enlarged when the object gets closer to the camera. The intensity of the foreground object in the scene image is distinctly different from the one in the training image. The proposed method also reliably detects the moving object.

In the experiments, we have also evaluated a set of the reverse test images, where the man wearing black clothes is used as the training foreground image and the girl wearing white clothes is used as the scene images. The resulting de-mixing vector is \[ w = [0.7065, -0.6422] \]. Similar results as the ones in Fig. 7 are also detected. The detection results reveal that the proposed ICA model with the PSO search generates similar de-mixing vectors, and the de-mixing vectors can be reliably used to detect various foreground objects, regardless of changes in object sizes and object intensities.

In addition, there is an interesting finding from the detection results in Fig. 7. When the foreground object is relatively very small in the scene image, the proposed method is sensitive to object shadows, as seen in Fig. 7(c3) and (h3). While the object size in the scene image gets larger, the shading effect becomes insignificant, as seen in Fig. 7(d3) and (g3).

D. Analysis of the Demixing Vector

As aforementioned, the 2-D demixing vector \[ w = [w_1, w_2] \] with \( w_1 \cdot w_2 < 0 \) from the proposed ICA model can be used as a convolution filter for the reference background and the
scene image. The conventional image difference method can also be treated as a \([1, -1]\) convolution filter. Foreground objects generally have more distinct gray-levels with respect to the background. Both image difference method and the proposed method can well detect foreground objects in an image sequence, but the image difference method is more sensitive to illumination changes. This is because the \([1, -1]\) filter results in a more distinct gray-level difference, compared to that of the proposed filter \(w = [w_1, w_2] \). In the experiments, we have evaluated numerous test sample images with varying reference backgrounds. The proposed ICA model with the PSO search consistently converges to a de-mixing vector similar to \([0.7641, -0.6452]\). Therefore, this vector can be treated as an optimal filter for background subtraction.

Let \(f_0(x, y)\) and \(f_1(x, y)\) be the gray levels at pixel coordinates \((x, y)\) of the reference background image and the scene image at frame \(t\), respectively. If

\[
\min \{f_0(x, y), f_1(x, y)\} < 1 - \max \{w_1, w_2\}
\]

then the response amplitude from the filter \([1, -1]\) is distinctly larger than that from the proposed filter \(w = [w_1, w_2]\) and, therefore, is more sensitive to noise and illumination changes. In the experiments, the filter is given by \([0.7641, -0.6452]\) from the proposed ICA model. It indicates that the gray-level ratio [the left-hand side of (9)] is less than 0.665 [the right-hand side of (9)], the \([1, -1]\) filter will generate a more significant amount of gray-level difference. Since most of the illumination changes in a scene background generally have a gray-level ratio smaller than 0.665, i.e., larger gray-level difference, it will detect both foreground objects and regions with significant illumination changes as foreground. This is why the bright window is intensified in Fig. 3(d) and detected as a foreground object in Fig. 4(d) when the simple image difference method is applied for foreground segmentation.

**IV. CONCLUSION**

Background subtraction is a widely used approach for detecting foreground objects in videos from a static camera. Indoor surveillance applications such as home-care and health-care monitoring, a motionless person should not be a part of the background. A reference background image without moving objects is, therefore, required for such applications. In this paper, we have presented an ICA-based background subtraction scheme for foreground segmentation. The proposed ICA model is based on the direct measurement of statistical independency that minimizes the difference between the joint PDF and the product of marginal PDFs, in which the probabilities are simply estimated from the relative frequency distributions. The proposed ICA model well performs the separation of highly-correlated signals.

The de-mixing vector \([0.7641, -0.6452]\) derived from the proposed ICA model can be considered as an optimal filter for background subtraction under arbitrary reference backgrounds. Since the de-mixing vector is only of a small size of \(1 \times 2\), its computation is as fast as the image difference method. Computation times in the detection stage of the proposed method are only 0.007 seconds (i.e., 142 fps) for a small 150 \(\times\) 200 image, and 0.09 seconds (i.e., 11 fps) for a large 640 \(\times\) 480 image on an AMD 64-bit 1.8-GHz personal computer. As seen in the experimental results, a part of the person’s body was missing due to the camouflage foreground in gray-level images. In order to eliminate the effect of camouflage, color may provide more information to discriminate a foreground object from its surrounding background. The ICA model that separates vector-valued signals in RGB color images is worth further investigation.

**REFERENCES**


Du-Ming Tsai received the B.S. degree in industrial engineering from Tunghai University, Taiwan, R.O.C., in 1981, and the M.S. and Ph.D. degrees in industrial engineering from Iowa State University, Ames, in 1984 and 1987, respectively.

From 1988 to 1990, he was a Principal Engineer of Digital Equipment Corporation, Taiwan branch, where his work focused on process and automation research and development. Currently, he is a Professor of industrial engineering and management at the Yuan-Ze University, Taiwan. His research interests include automated visual inspection, texture analysis, and visual surveillance.

Shia-Chih Lai received the B.S. degree in statistics from the Tunghai University, Taiwan, R.O.C., in 2004, and the M.S. degree in industrial engineering and management from the Yuan-Ze University, Taiwan, in 2006.

She is currently a researcher with Delta Electronics, Inc., Taiwan.