Density-Based Multi-Feature Background Subtraction with Support Vector Machine

Bohyung Han, *Member, IEEE,* Larry S. Davis, *Fellow, IEEE,*

Abstract—Background modeling and subtraction is a natural technique for object detection in videos captured by a static camera, and also a critical preprocessing step in various high level computer vision applications. However, there have not been many studies concerning useful features and binary segmentation algorithms for this problem. We propose a pixel-wise background modeling and subtraction technique using multiple features, where generative and discriminative techniques are combined for classification. In our algorithm, color, gradient and Haar-like features are integrated to handle spatio-temporal variations for each pixel. A pixel-wise generative background model is obtained for each feature efficiently and effectively by Kernel Density Approximation (KDA). Background subtraction is performed in a discriminative manner using a Support Vector Machine (SVM) over background likelihood vectors for a set of features. The proposed algorithm is robust to shadow, illumination changes, spatial variations of background. We compare the performance of the algorithm with other density-based methods using several different feature combinations and modeling techniques, both quantitatively and qualitatively.

Index Terms—Background modeling and subtraction, Haar-like features, support vector machine, kernel density approximation

1 Introduction

The identification of regions of interest is typically the first step in many computer vision applications including event detection, visual surveillance, and robotics. A general object detection algorithm may be desirable, but it is extremely difficult to properly handle unknown objects or objects with significant variations in color, shape and texture. Therefore, many practical computer vision systems assume a fixed camera environment, which makes the object detection process much more straightforward; a background model is trained with data obtained from empty scenes and foreground regions are identified using the dissimilarity between the trained model and new observations. This procedure is called *background subtraction*.

Various background modeling and subtraction algorithms have been proposed [1], [2], [3], [4], [5], which are mostly focused on modeling methodologies, but potential visual features for effective modeling have received relatively little attention. The study of new features for background modeling may overcome or reduce the limitations of typically used features, and the combination of several heterogeneous features can improve performance, especially when they are complementary and uncorrelated. There have been several studies for using texture for background modeling to handle spatial variations in the scenes; they employ filter responses, whose computation is typically very costly. Instead of complex filters, we select efficient Haar-like features [6] and gradient features to alleviate potential errors in background subtraction caused by shadow, illumination changes, and spatial and structural variations.

Model-based approaches involving probability density function are common in background modeling and subtraction, and we employ Kernel Density Approximation (KDA) [3], [7], where a density function is represented with a compact weighted sum of Gaussians, whose number, weights, means and covariances are determined automatically based on mean-shift mode-finding algorithm. In our framework, each visual feature is modeled by KDA independently and every density function is one-dimensional. By utilizing the properties of the 1D mean-shift mode-finding procedure, the KDA can be implemented efficiently because we need to compute the convergence locations for only a small subset of data.

When the background is modeled with probability density functions, the probabilities of foreground and background pixels should be discriminative, but it is not always true. Specifically, the background probabilities between features may be inconsistent due to illumination changes, shadow, and foreground objects similar in features to the background. Also, some features are highly correlated, i.e., RGB color features. So, we employ a Support Vector Machine (SVM) for non-linear classification, which mitigates the inconsistency and the correlation problem amongst features. The final classification between foreground and background is based on the outputs of the SVM.

There are three important aspects of our algorithm—integration of multiple features, efficient 1D density estimation by KDA and foreground/background classification by SVM. These are coordinated tightly to improve background subtraction performance. An earlier version of this research appeared in [8]; the current paper includes more comprehensive analysis of the feature sets and additional experiments.

- *B. Han is with the Department of Computer Science and Engineering, POSTECH, Korea. E-mail: bhhan@postech.ac.kr*
- *L. S. Davis is with the Department of Computer Science, University of Maryland, College Park, MD, USA. E-mail:lsd@cs.umd.edu*

2 Previous Work

The main objective of background subtraction is to obtain an effective and efficient background model for foreground object detection. In early years, simple statistics, such as frame differences and median filtering, were used to detect foreground objects. Some techniques utilized a combination of local statistics [9] or vector quantization [10] based on intensity or color at each pixel.

More advanced background modeling methods are density based, where the background model for each pixel is defined by a probability density function based on the visual features observed at the pixel during a training period. [11] modeled the background in YUV color space using a Gaussian distribution for each pixel. However, this method cannot handle multi-modal density functions, so is not robust in dynamic environments.

A mixture of Gaussians is another popular density-based method, which is designed for dealing with multiple backgrounds. Three Gaussian components representing the road, shadow, and vehicle are employed to model the background in traffic scenes in [12]. An adaptive Gaussian mixture model is proposed in [2], [13], where a maximum of K Gaussian components for each pixel are allowed but the number of Gaussians is determined dynamically. Also, variants of incremental EM algorithms have been employed to deal with real-time adaptation constraints of background modeling [14], [15]. However, a major challenge in the mixture model is the absence or weakness of strategies to determine the number of components; it is also generally difficult to add or remove components to/from the mixture [16]. Recently, more elaborate and recursive update techniques are discussed in [4], [5]. However, none of the Gaussian mixture models have any principled way to determine the number of Gaussians. Therefore, most real-time applications rely on models with a fixed number of components or apply ad-hoc strategies to adapt the number of mixtures over time [2], [4], [5], [13], [17].

Kernel density estimation is a non-parametric density estimation technique that has been successfully applied to background subtraction [1], [18]. Although it is a powerful representation for general density functions, it requires many samples for accurate estimation of the underlying density functions and is computationally expensive; so it is not appropriate for real-time applications, especially when high dimensional features are involved.

Most background subtraction algorithms are based on pixel-wise processing, but multi-layer approaches are also introduced in [19], [20], where background models are constructed at the pixel, region and frame levels and information from each layer is combined for discriminating foreground and background. In [21], several modalities based on different features and algorithms are integrated and a Markov Random Field (MRF) is employed for the inference procedure. The co-occurrence of visual features within neighborhood pixels is used for robust background subtraction in dynamic scenes in [22].

Some research on background subtraction has focused more on features than the algorithm itself. Various visual features may be used to model backgrounds, which include intensity, color, gradient, motion, texture, and other general filter responses. Color and intensity are probably the most popular features for background modeling, but several attempts have been made to integrate other features to overcome their limitations. There are a few algorithms based on motion cue [18], [23]. Texture and gradients have also been successfully integrated for background modeling [24], [25] since they are relatively invariant to local variations and illumination changes. In [26], spectral, spatial, and temporal features are combined, and background/foreground classification is performed based on the statistics of the most significant and frequent features. Recently, a feature selection technique was proposed for background subtraction [27].

3 Background Modeling and Subtraction Algorithm

This section describes our background modeling and subtraction method based on the 1D KDA using multiple features. KDA is a flexible and compact density estimation technique [7], and we present a faster method to implement KDA for 1D data. For background subtraction, we employ the SVM, which takes a vector of probabilities obtained from multiple density functions as an input.

3.1 Multiple Feature Combination

The most popular features for background modeling and subtraction are probably pixel-wise color (or intensity) since they are directly available from images and reasonably discriminative. Although it is natural to monitor color variations at each pixel for background modeling, they have several significant limitations as follows:

- They are not invariant to illumination changes and shadows.
- Multi-dimensional color features are typically correlated and joint probability modeling may not be advantageous in practice.
- They rely on local information only and cannot handle structural variations in neighborhoods.

We integrate color, gradient and Haar-like feature together to alleviate the disadvantages of pixel-wise color modeling. The gradient features are more robust to illumination variations than color or intensity features and are able to model local statistics effectively. So, gradient features are occasionally used in background modeling problems [26], [27]. The strength of Haar-like features lies in their simplicity and the ability to capture neighborhood information. Each Haar-like feature is weak by itself, but the collection of weak features has significant classification power [6], [28]. The integration of these features is expected to improve the accuracy of background subtraction. We have 11 features altogether, RGB color, 2 gradient features (horizontal and vertical) and 6 Haar-like features. The Haar-like features employed in our implementation are illustrated in Fig. 1. The Haar-like features are extracted from 9×9 rectangular

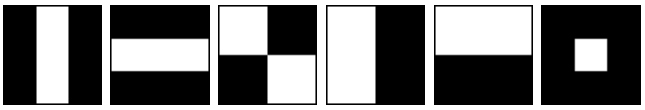


Fig. 1. Haar-like features for our background modeling

regions at each location in the image, while the gradient features are extracted with 3×3 Sobel operators. The 4th and 5th Haar-like features are similar to the gradient features, but differ in filter design, especially scale.

3.2 Background Modeling by KDA

The background probability of each pixel for each feature is modeled with a Gaussian mixture density function.[1] There are various methods to implement this idea, and we adopt KDA, where the density function for each pixel is represented with a compact and flexible mixture of Gaussians. The KDA is a density approximation technique based on mixture models, where mode locations (local maxima) are detected automatically by the mean-shift algorithm and a single Gaussian component is assigned to each detected mode. The covariance for each Gaussian is computed by curvature fitting around the associated mode. More details about KDA are found in [7], and we summarize how to build a density function by KDA for 1D case.

Suppose that training data for a sequence are composed of n frames and $x_{F,i}$ $(i = 1, \ldots, n)$ is the i-th value for feature F at a certain location. Note that the index for pixel location is omitted for simplicity. For each feature, we first construct a 1D density function at each pixel by kernel density estimation based on Gaussian kernel as follows:

$$\hat{f}_F(x) = \frac{1}{\sqrt{2\pi}} \sum_{i=1}^{n} \frac{\kappa_{F,i}}{\sigma_{F,i}} \exp\left(-\frac{(x - x_{F,i})^2}{2\sigma_{F,i}^2}\right), \qquad (1)$$

where $\sigma_{F,i}$ and $\kappa_{F,i}$ are the bandwidth and weight of the i-th kernel, respectively.

As described above, the KDA finds local maxima in the underlying density function (Eq. (1)), and a mode-based representation of the density is obtained by estimating all the parameters for a compact Gaussian mixture. The original density function is simplified by KDA as

$$\tilde{f}_F(x) = \frac{1}{\sqrt{2\pi}} \sum_{i=1}^{m_F} \frac{\tilde{\kappa}_{F,i}}{\tilde{\sigma}_{F,i}} \exp\left(-\frac{(x - \tilde{x}_{F,i})^2}{2\tilde{\sigma}_{F,i}^2}\right), \qquad (2)$$

where $\tilde{x}_{F,i}$ is a convergence location by the mean-shift mode finding procedure, and $\tilde{\sigma}_{F,i}$ and $\tilde{\kappa}_{F,i}$ are the estimated standard deviation and weight for the Gaussian assigned to each mode, respectively. Note that the number of component in Eq. (2), m_F, is generally much smaller than n.

One remaining issue is bandwidth selection—initialization of $\sigma_{F,i}$—to create the original density function in Eq. (1). Although there is no optimal solution for bandwidth selection for the nonparametric density estimation, we initialize the kernel bandwidth based on the median absolute deviation over the temporal neighborhood of the corresponding pixels, which is almost identical to the method proposed in [1]. Specifically, the initial kernel bandwidth of the i-th sample for feature F is given by

$$\sigma_{F,i} = \max\left(\sigma_{min}, \mathrm{med}_{t=i-t_w,\ldots,i+t_w} |x_{F,t} - x_{F,t-1}|\right), \quad (3)$$

where t_w is the temporal window size and σ_{min} is the predefined minimum kernel bandwidth to avoid too narrow a kernel. The motivation for this strategy is that multiple objects may be projected onto the same pixel, but feature values from the same object would be observed for a period of time; the absolute difference between two consecutive frames, therefore, does not jump too frequently.

Although KDA handles multi-modal density functions for each feature, it is still not sufficient to handle long-term background variations. We must update background models periodically or incrementally, which is done by Sequential Kernel Density Approximation (SKDA) [7]. The density function at time step $t + 1$ is obtained by the weighted average of the density function at the previous time step and a new observation, which is given by

$$\hat{f}_F^{t+1}(x) = (1 - r)\hat{f}_F^t(x) + \frac{r\tilde{\kappa}_{F,i}^{t+1}}{\sqrt{2\pi}\tilde{\sigma}_{F,i}^{t+1}} \exp\left(-\frac{(x - \tilde{x}_{F,i}^{t+1})^2}{2(\tilde{\sigma}_{F,i}^{t+1})^2}\right), \quad (4)$$

where r is a learning rate (forgetting factor). To prevent the number of components from increasing indefinitely by this procedure, KDA is applied at each time step. The detailed technique and analysis are described in [7]. Since we are dealing with only 1D vectors, the sequential modeling is also much simpler and similar to the one introduced in Section 3.3; it is sufficient to compute the new convergence points of the mode locations immediately before and after the new data in the density function at each time step.[2] The computation time of SKDA depends principally on the number of iterations for the data points in Eq. (4), and can vary at each time step.

3.3 Optimization in One Dimension

We are only interested in 1D density functions, and the convergence of each sample point can be obtained much faster than the general case. Given 1D samples, x_i and x_j $(i, j = 1, \ldots, n)$, the density function created by kernel density estimation has the following properties:

$$(x_i \leq x_j \leq \hat{x}_i) \vee (x_i \geq x_j \geq \hat{x}_i) \Rightarrow \hat{x}_i = \hat{x}_j \qquad (5)$$

where $\hat{x}_i$ and $\hat{x}_j$ are the convergence location of x_i and x_j, respectively. In other words, all the samples located between a sample and its associated mode converge to the same mode location. So, every convergence location in the underlying density function can be found without running

1. Histogram-based modeling is appropriate for 1D data. However, the construction of a histogram at each pixel requires significant memory and the quantization is not straightforward due to the wide range of Haar-like feature values. Also, a histogram is typically less stable than continuous density functions when only a small number of samples are available.

2. Strictly speaking, it may be sometimes necessary to compute the convergences at more locations due to a cascaded merges.

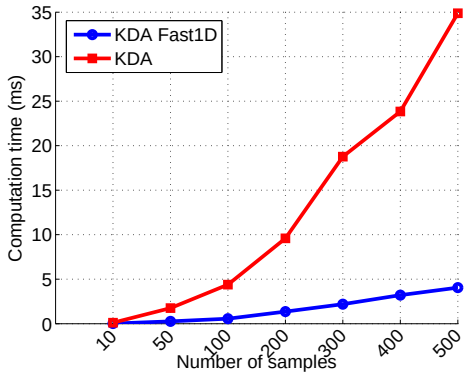


Fig. 2. Computation time comparison between the original KDA and KDA with 1D optimization.

the actual mode-finding procedure for all the sample points, which is the most expensive part in the computation of KDA. This section describes a simple method to find all the convergence points by a single linear scan of samples using the above properties, efficiently.

We sort the sample points in ascending order, and start performing mean-shift mode finding from the smallest sample. When the current sample moves in the gradient ascent direction by the mean-shift algorithm in the underlying density function and passes another sample's location during the iterative procedure, we note that the convergence point of the current sample must be the same as the convergence location of the sample just passed, terminate the current sample's mean-shift process, and move on to the next smallest sample, where we begin the mean-shift process again.[3] If a mode is found during the mean-shift iterations, its location is stored and the next sample is considered. After finishing the scan of all samples, each sample is associated with a mode and the mode-finding procedure is complete. This strategy is simple, but improves the speed of mean-shift mode-finding significantly, especially when many samples are involved. Fig. 2 illustrates the impact of 1D optimization for the mode-finding procedure, where a huge difference in computation time between two algorithms is evident.

3.4 Foreground and Background Classification

After background modeling, each pixel is associated with k 1D Gaussian mixtures, where k is the number of features integrated. Background/foreground classification for a new frame is performed using these distributions. The background probability of a feature value is computed by Eq. (2), and k probability values are obtained from each pixel, which are represented by a k-dimensional vector. Such k-dimensional vectors are collected from annotated foreground and background pixels, and we denote them by $\mathbf{y}_j$ $(j = 1, \ldots, N)$, where N is the number of data points.

3. This can be implemented using a reference variable. If a sample is moving backward, its convergence location is the same as the previous one. If a sample is moving forward, its convergence location can be set when the next mode is found.

In most density-based background subtraction algorithms, the probabilities associated with each pixel are combined in a straightforward way, either by computing the average probability or by voting for the classification. However, such simple methods may not work well under many real-world situations due to feature dependency and non-linearity. For example, pixels in shadow may have a low background probability in color modeling unless shadows are explicitly modeled as transformations of color variables, but high background probability in texture modeling. Also, the foreground color of a pixel can look similar to the corresponding background model, which makes the background probability high although the texture probability is probably low. Such inconsistency among features is aggravated when many features are integrated and data is high-dimensional, so we train a classifier over the background probability vectors for the feature set, $\{\mathbf{y}_j\}_{1:N}$. Another advantage to integrating the classifier for foreground/background segmentation is to select discriminative features and reduce the feature dependency problem; otherwise, highly correlated non-discriminative features may dominate the classification process regardless of the states of other features.

An SVM is employed for the classification of background and foreground. We used a radial basis function kernel to handle non-linear input data, and used approximately 40K data points (10K for foreground and 30K for background) for training. Note that a universal SVM is used in our method for all sequences—not a separate SVM for each pixel nor for each sequence; this is possible because we learn the classifier based on probability vectors rather than feature vectors directly. A similar approach is introduced in [29], where the magnitude of optical flow and inter-frame image difference are used as features for classification. However, the 2D features have limitation in handling dynamic and multi-modal scenes properly—e.g., stationary foreground and moving background, Other background subtraction methods using SVM require per-pixel (or per-block) classifiers and separate training for each sequence [30], [31] since they apply SVM to the original feature space, so they need many frames for training and significant memory space to store many SVM classifiers.

Fig. 3 summarizes the training procedure for background subtraction; the density-based background model is constructed for each feature, and the SVM is trained using background probability vectors and binary labels annotated from validation frames. For testing, a background probability vector for each pixel is computed based on the modeled backgrounds, and the trained SVM is applied to the vector for classification. We emphasize that the sequences used for training are separate from the testing sequences and that the SVM does not need to be re-trained to be applied to a new input sequence.

4 Experiments

We present the performance of our background modeling and subtraction algorithm using real videos. Each sequence involves challenges such as significant pixel-wise noises

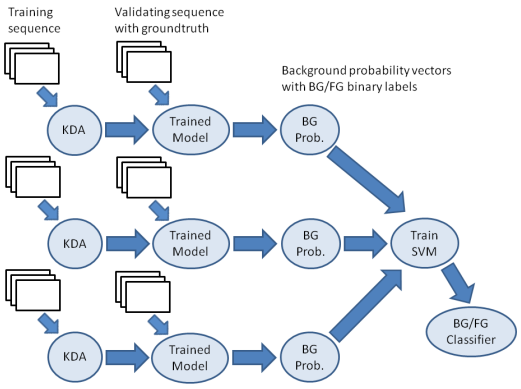


Fig. 3. Diagram for training procedure. Note that we use pixel-wise density functions by KDA but train a single common SVM for all pixels and all sequences.

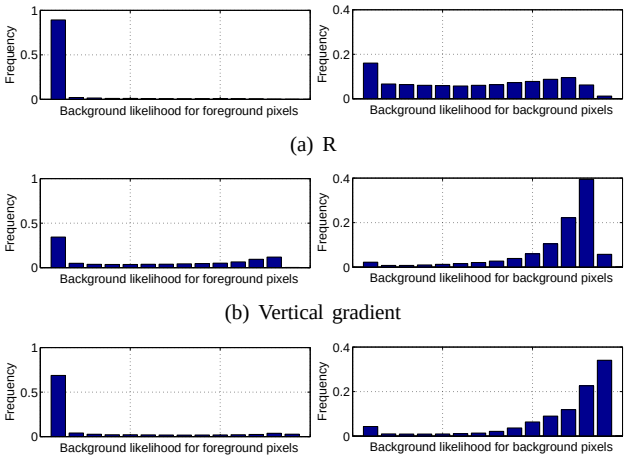
	R	G	B	H1	H2	H3	H4	H5	H6	dx	dy
R	1.00	0.97	0.94	0.79	0.77	0.01	0.00	0.00	0.88	0.00	0.01
G	0.84	1.00	0.98	0.80	0.78	0.00	0.01	0.00	0.90	0.00	0.01
B	0.74	0.73	1.00	0.79	0.76	0.00	0.00	0.02	0.88	0.01	0.01
H1	0.67	0.67	0.63	1.00	0.88	0.01	0.01	0.00	0.96	0.01	0.00
H2	0.66	0.66	0.63	0.84	1.00	0.00	0.00	0.01	0.95	0.01	0.00
H3	0.42	0.42	0.41	0.56	0.55	1.00	0.01	0.00	0.00	0.00	0.00
H4	0.53	0.52	0.51	0.70	0.67	0.69	1.00	0.00	0.00	0.57	0.00
H5	0.50	0.50	0.49	0.64	0.65	0.71	0.69	1.00	0.01	0.00	0.55
H6	0.61	0.61	0.59	0.82	0.83	0.53	0.65	0.61	1.00	0.01	0.00
dx	0.48	0.48	0.47	0.55	0.53	0.56	0.71	0.57	0.50	1.00	0.02
dy	0.46	0.46	0.46	0.51	0.52	0.53	0.56	0.65	0.48	0.61	1.00

Fig. 4. Correlations between features. The upper triangular matrix illustrates the correlation coefficients between feature values while the lower triangular matrix represents the correlation coefficients between background likelihoods of features.

(*subway*), dynamic background of a water fountain (*fountain*) and reflections and shadow in wide area (*caviar* [32]).

4.1 Feature Analysis

We describe the characteristics of individual features and the performance of multiple feature integration. Fig. 4 illustrates the correlation between every pair of features. RGB colors and three Harr-like features are significantly correlated, and the 4th and 5th Haar-like features have non-trivial correlation with vertical and horizontal gradient features, respectively, as one would expect. However, note that the correlations between background likelihoods of even highly correlated features are not so strong, which explains why there are still benefits of integrating highly correlated features. Fig. 5 illustrates the discriminativeness of features for foreground/background classification. The histograms of background probabilities for foreground and background pixels are presented for three different features—a representative feature for color, gradient and Haar-like feature. According to Fig. 5, color features have



(a) R

(b) Vertical gradient

(c) The first Haar-like feature

Fig. 5. Feature performance for classification. The histograms of background probabilities for foreground and background pixels are presented for each feature. Note that, in the ideal case, foreground should have low background probabilities only and background pixels should have high background probability only.

substantially poor quality, compared with the other two features; background probabilities for background pixels vary significantly, which makes it difficult to classify them correctly. Also, background probabilities of gradient features for foreground pixels are widespread.

The combination of heterogeneous features improves background/foreground classification performance. Recall that the R feature has mediocre quality for background subtraction. The inclusion of the G feature does not help much (Fig. 6(a)) because background probabilities of pixels in these two feature bands are highly correlated. However, this problem is alleviated when gradient or Haar-like feature are integrated; foreground and background pixels are now more separable, so that classification is more straightforward (Fig. 6(b) and 6(c)).

4.2 Evaluation of Background Subtraction

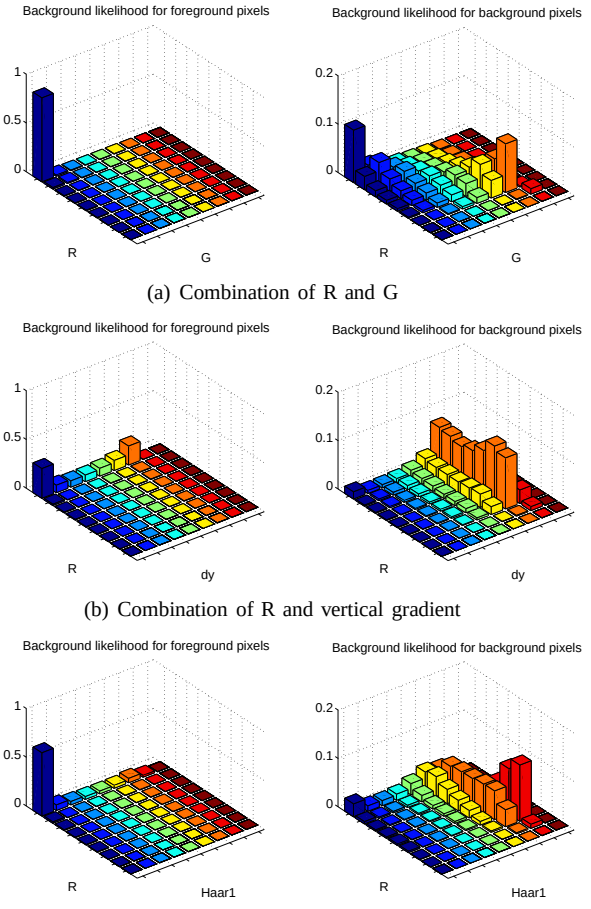
The performance of our background subtraction algorithm is evaluated in various ways. For quantitative evaluation, Precision-Recall (PR) curves are employed, where the precision and recall are defined as

$$precision = \frac{n(B_T \cap B_{BGS})}{n(B_T)} \quad (6)$$

$$recall = \frac{n(F_T \cap F_{BGS})}{n(F_T)}, \quad (7)$$

respectively, where F_T and B_T are the groundtruth sets of foreground and background pixels, and F_{BGS} and B_{BGS} denote the sets of foreground and background pixels obtained by a background subtraction algorithm.

We first compared our algorithm with other density-based techniques such as Gaussian Mixture Model (GMM) [5] and Kernel Density Estimation (KDE) [1] based on RGB



(a) Combination of R and G

(b) Combination of R and vertical gradient

(c) Combination of R and the first Haar-like feature

Fig. 6. Improvement of discriminativeness by adding heterogeneous features—gradient or Haar-like features. Note that the combination of R and G may not improve classification performance compared with R only. (See also Fig. 5(a).) However when the vertical gradient or the 1st Haar-like feature are combined with R feature, the characteristics of foreground pixels become quite different from those of background pixels.

color feature only. For the GMM method, we downloaded the code for [5] and tested two versions—with and without shadow detection. In our experiments, our algorithm with SVM (KDA+RGB+Grad+Haar) is noticeably better than KDE and GMM with/without shadow detection as shown in Fig. 7. Additionally, we implemented KDE with all 11 features and SVM (KDE+RGB+Grad+Haar) and obtained comparable accuracy to our technique, which suggests the performance of KDA with respect to KDE.[4] Note that the range of $0.9 \sim 0.95$ in both precision and recall is critical to actual performance in background subtraction.

The performance of several different feature sets are compared and illustrated in Fig. 8. Our algorithm with all three features (RGB+Grad+Haar) has the best performance for all three sequences. The RGB+Grad shows better results

4. The performances of KDA and GMM are similar in RGB space with almost identical implementations of both algorithms except density estimation, which is shown by pink line in Fig. 7 and red line in Fig. 9(b).

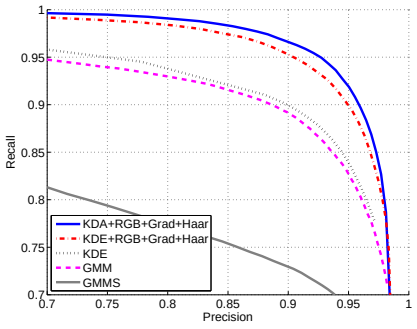
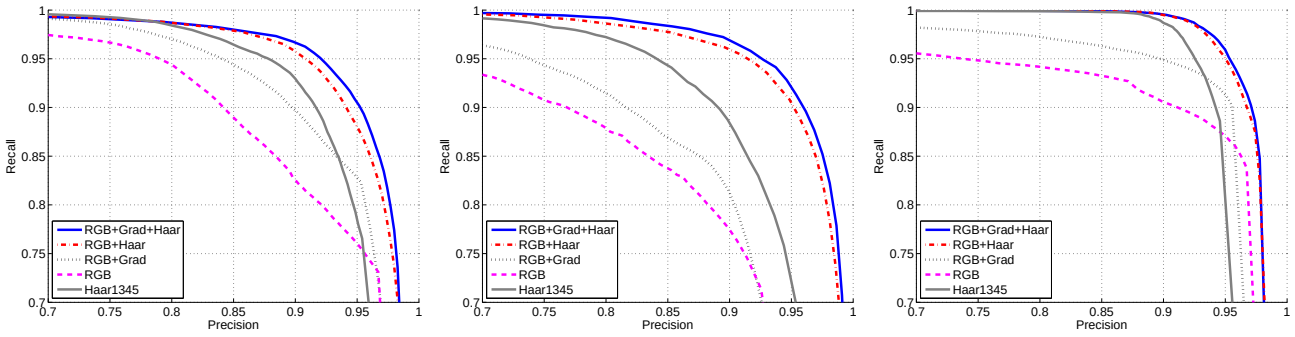


Fig. 7. PR curves for different density estimations

than RGB only, and the performance of RGB+Haar is comparable to RGB+Grad+Haar; the integration of gradient feature is not very useful due to the correlation and similarity with related Haar-like features. However, the combination of the correlated features still improves the classification performance non-trivially in the *subway* and the *fountain* sequence since the SVM plays a role to select proper features implicitly. We also tested our algorithm using 4 independent Haar-like features based on the result in Fig. 4, where RGB features are excluded since they are significantly correlated with some of the selected Haar-like features. The accuracy based on the independent Haar-like features is significantly lower than full feature combination.

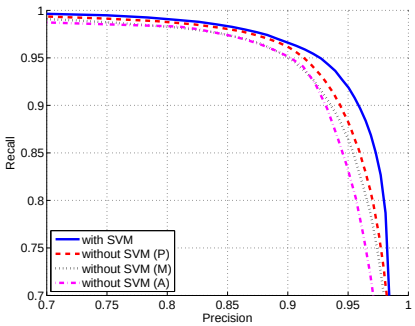
The importance of the SVM to foreground/background segmentation was tested, and Fig. 9 illustrates the SVM improves classification. Three other simple classifiers are employed for comparison; the product (P), minimum (M) and sum (S) of probabilities for multiple features are computed and predefined thresholds are applied for classification. SVM is particularly useful for high-dimensional data; it is probably because the high-dimensional data have more non-linear characteristics and it is more difficult to classify such data accurately with simple methods. Note that the performance of the SVM for correlated RGB is not good as presented in Fig. 9(b). Fig. 10 presents the background likelihood at each pixel, and provides a clear idea about the reason for better classification; the SVM tends to handle dynamic backgrounds and shadow better. Another advantage observed in Fig. 10 is that background likelihoods of foreground and background pixels are separated better by the SVM, and the classification is not very sensitive to threshold value. We also tested how the performance of SVM changes with different kernels, but did not observe any noticeable differences.

Qualitative results for comparison of background subtraction algorithms are presented in Fig. 11. The threshold for each algorithm is set to have 95% precision in classification. Fig. 11 shows our algorithm also has good qualitative performance compared with the other two. The performance of feature combinations are evaluated qualitatively and presented in Fig. 12. The combination of color, gradient and Haar-like features outperforms other feature sets in segmentation, especially when shadows, reflections and dynamic backgrounds—tree branches and leaves in the

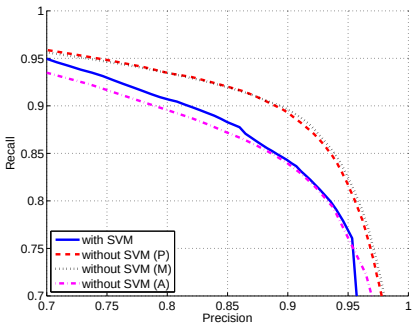


(a) *subway* sequence (b) *fountain* sequence (c) *caviar* sequence

Fig. 8. PR curves of our algorithms with several different feature sets.

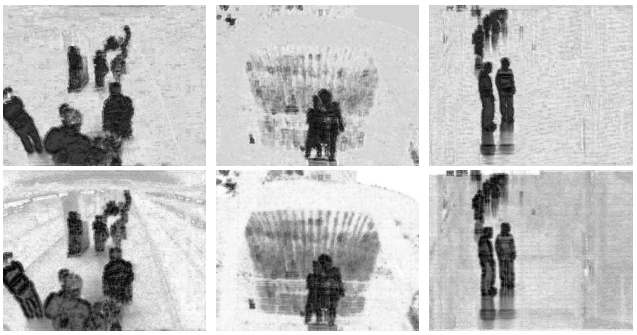


(a) RGB+Grad+Haar



(b) RGB

Fig. 9. PR curves for testing the contribution of SVM.



(a) *subway* sequence (b) *fountain* sequence (c) *caviar* sequence

Fig. 10. Background likelihood (top) with and (bottom) without SVM. Bright pixels have higher BG likelihoods.

rightmost area in the *outdoor* sequence—are involved.

Our algorithm runs at 0.1 frame/sec in the standard PC with Intel i7 2.13GHz CPU and 2GB memory, which is tested for 320×240 image with MATLAB implementation.

5 Conclusion

We have introduced a multiple feature integration algorithm for background modeling and subtraction, where the background is modeled with a generative method and background and foreground are classified by a discriminative technique. KDA is used to represent a probability density function of the background for RGB, gradient, and Haar-like features in each pixel, where 1D independent density functions are used for simplicity. For classification, an SVM based on the probability vectors for the given feature set is employed. Our algorithm demonstrates better performance than other density-based techniques such as GMM and KDE, and the performance is tested quantitatively and qualitatively using a variety of indoor and outdoor videos.

Acknowledgments

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2011-0005749).

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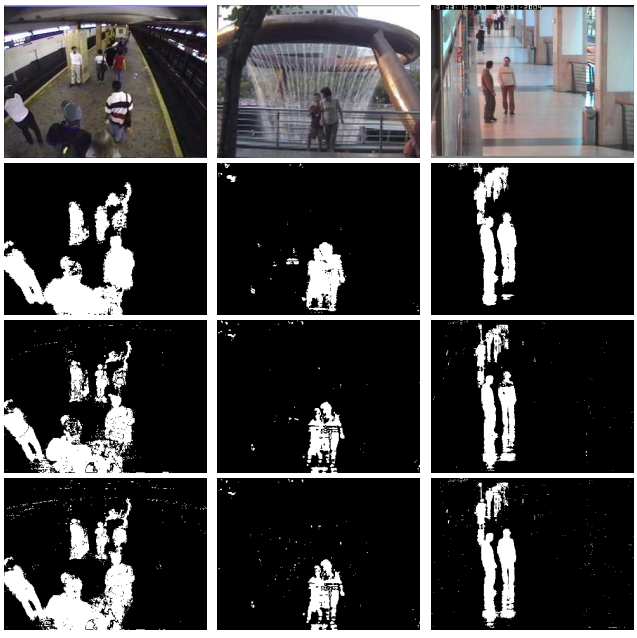

(a) *subway* sequence (b) *fountain* sequence (c) *caviar* sequence

Fig. 11. Background subtraction results of three algorithms. From top to bottom, the original images and the results of our method, KDE and GMM are presented. Note that there is a moving car on the left side of the child in the *fountain* sequence, which is clearly visible in our algorithm but not detected by KDE or GMM.

(a) *caviar2* sequence (b) *outdoor* sequence (c) *indoor* sequence

Fig. 12. Background subtraction results for three different feature sets. From top to bottom, results with RGB+Grad+Haar, RGB+Grad, and RGB are illustrated. Note that various challenges such as reflection, shadow, dynamic background, etc. are handled effectively by our algorithm with the new feature set.

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