Robust Baggage Detection and Classification Based on Local Tri-directional Pattern

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Abstract—In recent decades, the automatic video surveillance system has gained significant importance in computer vision community. The crucial objective of surveillance is monitoring and security in public places. In the traditional Local Binary Pattern, the feature description is somehow inaccurate, and the feature size is large enough. Therefore, to overcome these shortcomings, our research proposed a detection algorithm for a human with or without carrying baggage. The Local tri-directional pattern descriptor is exhibited to extract features of different human body parts including head, trunk, and limbs. Then with the help of support vector machine (SVM), extracted features are trained and evaluated. Experimental results on INRIA and MSMT17_V1 datasets show that LtriDP outperforms several state-of-the-art feature descriptors and validate its effectiveness.

Index Terms—Carrying baggage detection and classification, Local tri-directional Pattern, Support Vector Machine, Boosting Machine, Video Surveillance.

I. INTRODUCTION

These days computer vision approaches have a potential impact on many intelligent surveillance systems. These approaches mainly involve knowledge, integration and management [1], [2]. Most of the detection system face some serious shortcomings like illumination conditions and complex backgrounds, and to deal with these, several approaches in the past has been proposed. In this proposed framework an effort is contributed, which attains the baggage information concerning the body of the human carrying it. Ideally it can be achieved by analysing the human in different postures while carrying bag and it deals with various texture patterns of the baggage.

A. Contributions

The primary contribution of our study is
• Handled the diverse texture patterns.
• And then the Local tri-directional Pattern descriptor is applied which provide information regarding the local intensities and provide accurate feature description and feature size.
• Finally, the SVM classifier is used to sum up the final results and substantiate the presence of baggage in the human region.

B. Organization

This paper is alienated into the following segments. Section II explains the literature review of the work which had been done; Section III explains the Preprocessing Techniques. Section IV explains the descriptor which is used in our framework. Section V explains the Classification strategy of SVM. Section VI explains the experimental results of the proposed scheme. Section VII concludes our results.

II. RELATED WORK

For the detection and classification of abandoned baggage, several approaches have been proposed. Haralick et al., suggested the Gray level co-occurrence matrix (GLCM) for image classification [3], [4]. Features are extracted on the basis of co-occurrence matrix. Zhang et al. suggested a framework that uses Prewitt edge detector to extract the texture features, and isolates co-occurrence matrix for those edge images as a substitute of original images [5]. At some points in order to extract the features, wavelet packets are used [6]. For the image retrieval and texture classification Gabor filter was also used [7]. The concatenation of Rotation invariant feature vector and Gabor filter has been used for content based image retrieval [8]. Wahyono et al. [9], [10] proposed a novel approach for the detection and classification of baggage and they utilize the three-dimensional information based on the human body carrying baggage. For the baggage detection Fuzzy-Model based integration framework is used and the features are then classified by using support vector machine. The results indicates that the proposed framework is one of the solutions of video surveillance system. K. Kim, et al. [11] proposed object recognition framework for different kinds of objects. Different image processing techniques and selective image methods are used to improve the image quality. The performance evaluation shows some promising results while minimizing the error rate and improving accuracy for training and testing samples. T. Khanam et al. and Rajesh Kumar Tripathi et al. [12], [15], [20], [23] proposes a detection and classification framework for the baggage by using the boosting strategy along with dynamic body parts. The techniques like background subtraction, HSI model, RSD-HOG features are used to deal with the challenges faced. Experimental results are better as compared to other alternatives. T. F. Ju et al. [16] proposed a vision-based object detection framework by using RADAR and LIDAR. This technique has faced several challenges like false alarm rate etc. but this paper presents an enhanced robustness in terms of vision-based object detection. W. Rakumthong et al. and Y. Tsung et al. [17], [18] proposed a framework for the boosted multiclass object detection. The results reveal that the proposed framework gives high detection rate like 90%.
III. THE PROPOSED METHOD

A. An overview

This section presents the framework for the detection of human and baggage in an image which is shown in Figure 1. Histogram equalization technique is used in order to enhance the input images. It enhances the contrast and removes noise to increase image visual quality. Then Local tri-directional Pattern is applied on the human body part samples and baggage samples to extract features. From this, three histograms are formed, two from pattern information and one from magnitude pattern. The final decision involves concatenating the features extracted from tri-directional pattern and magnitude pattern.

B. Contrast Enhancement

For the contrast enhancement histogram equalization is used where the histogram of the resultant image is as flat as up to the extent. In other words, histogram equalization involves probability theory, and it is treated as the probability distribution of the gray levels. Let’s suppose $I$ to be an image whose pixel values are $ I(x, y)$. It is composed of $L$ discrete gray levels denoted by: $ \{I_0, I_1, \ldots, I_{L-1}\}$. Here, $ I(x, y)$ represents the intensity of the image at a spatial location $(x, y)$ with the condition that $ I(x, y) \in \{I_0, I_1, \ldots, I_{L-1}\}$. The histogram of a digital image is a discrete function because intensities are all discrete values, Histogram $h$ is defined as

$$ h(I_k) = n_k, \quad \text{for } k = 0, 1, 2, \ldots, L - 1 \quad (1) $$

Where $k$-th gray level is denoted as $I_k$ and number of times gray level $I_k$ appears in the image is represented as $n_k$. Basically, it is said that histogram is the frequency of occurrence of the gray levels in the image.

$$ f(I) = \sum_{x=0}^{L} h|x| = H|I| \quad (2) $$

The intensity values in an image are considered as random values between 0 and $(L - 1)$. For normalization use Equation

$$ Z_x = (I - \text{Min}) \frac{255}{\text{Max} - \text{Min}} \quad (3) $$

Where $\text{Min} = 0, \text{Max} = (L - 1)$. To find the probability of the random pixel values following formula is used [19].

$$ P_k = \frac{\text{pixels with intensity } k}{\text{total pixels}} \quad (4) $$

IV. FEATURE DESCRIPTOR

A. Local tri-directional Pattern Descriptor

Local tri-directional pattern is an powerful variant of Local Binary Pattern (LBP) and it does not contain uniform relationship with the neighbouring pixels. It regulates in various directions while forming relationship with the neighbouring pixels. Most of the times, 3 directions are involved in tri-directional pattern which are shown in Figure 2. Like the LBP, each centre pixel is surrounded by 8 neighbouring pixels and each neighbouring pixel is compared by the centre pixel and with the two contiguous neighbouring pixels. The two contiguous neighbouring pixels can be horizontal and vertical and the detailed pattern information is exhibited in Figure 2 and explained statistically in the following equations [21], [22].
Lets suppose, $I_c$ as centre pixel, surrounded by 8-neighbourhood pixels $I_1, I_2, I_3, I_4, I_5, I_6, I_7, \text{ and } I_8$. Firstly, difference of each neighborhood pixel with centre pixel is calculated.

$$D_1 = I_i - I_8, D_2 = I_i - I_{i+1}, D_3 = I_i - I_c$$

$$\forall i = 2, 3, 4, \ldots, 7$$

$$D_1 = I_i - I_8, D_2 = I_i - I_{i+1}, D_3 = I_i - I_c$$ for $i = 1$  \,(6)

$$D_1 = I_i - I_{i-1}, D_2 = I_i - I_1, D_3 = I_i - I_c$$ for $i = 8$  \,(7)

Now $D_1$, $D_2$ and $D_3$ are the three differences of the neighbouring pixel with the centre pixel and further patterns are formed based on these differences. Each neighbouring pixel $i = 1, 2, \ldots, 8$, the values of $f_i(D_1, D_2, D_3)$ is calculated using Equation \,(7) and finally the tri-directional pattern has been obtained. To get the ternary pattern for each centre pixel, we use Equation \,(8) and then convert it into two binary patterns.

$$LTriDP_i (I_c) = \{f_1, f_2, f_3, \ldots, f_8\}$$ \,(8)

$$LTriDP_1 (I_c) = \{S_3 (f_1), S_3 (f_2), S_3 (f_3), \ldots, S_3 (f_8)\}$$

$$S_3(x) = \begin{cases} 
1, & \text{when } x = 1 \\
0, & \text{else}
\end{cases}$$

$$LTriDP_2 (I_c) = \{S_4 (f_1), S_4 (f_2), S_4 (f_3), \ldots, S_4 (f_8)\}$$

$$S_4(x) = \begin{cases} 
1, & \text{when } x = 2 \\
0, & \text{else}
\end{cases}$$

$$LTriDP (I_c)_{l=1,2} = \sum_{i=0}^{7} 2^l \times LTriDP_i (I_c) (l + 1)$$ \,(11)

Then we get the map, and histograms are calculated by using Equation \,(2) for both the binary patterns. Tri-directional pattern is used to get the local valuable data, but to extract more information, more informative feature vectors are required. For this, magnitude pattern becomes very effective, and it is achieved through centre pixel, its neighbourhood pixel and two most contiguous pixels. Following equations show the results of magnitude patterns.

$$M_1 = \sqrt{(I_{i-1} - I_c)^2 + (I_{i+1} - I_c)^2}$$ \,(12)

$$M_1 = \sqrt{(I_{i-1} - I_i)^2 + (I_{i+1} - I_i)^2} \forall i = 2, 3, \ldots, 7 $$ \,(13)

$$M_1 = \sqrt{(I_8 - I_c)^2 + (I_1 - I_c)^2}$$ \,(14)

$$M_1 = \sqrt{(I_8 - I_c)^2 + (I_1 - I_c)^2} \text{ for } i = 1$$ \,(15)

The values of the magnitude pattern $M_1$ and $M_2$ are calculated for each neighbouring pixel and are assigned accordingly to each neighbouring pixel.

$$Mag_i(M_1, M_2) = \begin{cases} 
1, & \text{when } M_1 \geq M_2 \\
0, & \text{else}
\end{cases}$$ \,(16)

$$LTriDP_{mag} (I_c) = \{Mag_1, Mag_2, Mag_3, \ldots, Mag_8\}$$ \,(17)

$$LTriDP (I_c)_{mag} = \sum_{i=0}^{7} 2^l \times LTriDP_{mag} (I_c)$$ \,(18)

At that point too, the histograms are created by using Equation \,(2) At the end, three feature vectors are created, two from directional pattern and one from magnitude pattern. All the three feature vectors are concatenated into one feature vector and a 150-dimensional feature vector is formed. For training and testing, we manually classified image samples as testing samples and training samples. For training purposes, the images are taken as three categories:

$$X = [His \mid LTriDP_1 \mid LTriDP_2 \mid LTriDP_{mag}]$$ \,(19)

\section{Classification}
In the domain of image analysis, support vector machine is considered as most commonly deployed classifier.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{image1.png}
\caption{Baggage Placement Samples which are used in our work (Duffel Bag, Travel Pack or Wheeled Luggage, Bag pack).}
\end{figure}

It finds the best distinction among different classes, as it splits the positive and negative categories with supreme space for a given training set.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{image2.png}
\caption{Samples used for Training Purpose.}
\end{figure}

The images selected for the training purpose are those which contains human with carrying bag or human without carrying
VI. EXPERIMENTAL RESULTS

In this framework, techniques are implemented using Matrix Laboratory (MATLAB) which provides ability to implement the algorithm in a high-level programming language with built-in Visualization Toolbox.

TABLE I: Results of SVM Classifier with different Kernel functions.

| Validation scheme          | SVM Kernel | Accuracy |
|----------------------------|------------|----------|
| 70 − 30 validation        | Linear     | 94.5%    |
|                            | Quadratic  | 94%      |
|                            | Gaussian   | 95.5%    |
|                            | Cubic      | 95.1%    |
| 10-Fold Cross Validation   | Linear     | 95.5%    |
|                            | Quadratic  | 95%      |
|                            | Gaussian   | 94%      |
|                            | Cubic      | 94.1%    |

The presented approach was first analyzed to classify that the image regions having human are either with baggage or without baggage. The samples with carrying bag are considered to be as positive samples and those image samples in which human without carrying bag are negative samples. For instance, given a training data \( n \) and it belongs to 1 or -1 depends upon which class of the feature vector. It can be considered as a body with baggage 1 and body without baggage -1. The training scheme of 70-30% validation and 10-fold cross validation is used for the validation of results. The results after applying SVM classifier with different kernel functions on the image set is shown in Table I.

And Table II illustrates the assessment on the basis of accuracy and other evaluation parameters like Precision, Recall, Specificity and Sensitivity with state of the art methods. The results presented refers that the proposed method has the highest precision, recall and accuracy rates as compared to other approaches. The formulas used for computing the Precision, Recall, Specificity and Sensitivity are given below:

\[
Precision = \frac{TP}{TP + FP} \quad (20)
\]

\[
Recall = \frac{TP}{TP + FN} \quad (21)
\]

\[
Specificity = \frac{TN}{TN + FP} \quad (22)
\]

\[
Sensitivity = \frac{TP}{TP + FN} \quad (23)
\]

The confusion matrix and ROC Curve of the proposed framework is shown in Figure 5 and Figure 6.

VII. CONCLUSION

In this study, an approach is proposed for the detection of human and baggage with the vision of ensuring security in public places. This approach deals with the human body parts and the baggage and utilizes a strong relationship between them. To improve the contrast of the image, histogram equalization is used. The proposed approach attains the three-dimensional information of the baggage from the body of the human carrying it. On the extracted regions Local tri-directional Pattern is applied and get feature vectors. Finally, the extracted feature vectors of pattern information and magnitude information are concatenated into one feature vector and trained by the Boosting Support Vector Machine (SVM). After conducting extensive experiments, the proposed system shows a satisfactory classification accuracy rate of 95%. One of the limitations of this framework is that, it fails to detect...
TABLE II: Evaluation of Training Dataset and comparison with other state the art methods.

| Category | Class. Accuracy | Precision | Recall/TPR | Specificity | Sensitivity | FPR |
|----------|-----------------|-----------|------------|-------------|-------------|-----|
| OUR      | 95%             | 0.9889    | 0.9511     | 0.8333      | 0.9         | 0.8997 |
| [23]     | 90.26%          | 0.9179    | 0.703      | 0.7764      | –           | –    |
| [20]     | 88.27%          | 0.9071    | 0.9151     | 0.8252      | –           | –    |
| [17]     | 81.00%          | 0.8100    | 0.7700     | –           | –           | –    |
| [10]     | 79.86%          | 0.8121    | 0.8200     | –           | –           | –    |

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Baggage in much occluded state where objects are not visually separable. Basically, in such occluded state it is not possible to detect the edges. However, potential promotion of these limitations will improve the system performance in a very notable time.

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