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OBJECT DETECTION USING AM-FM FEATURES

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***Abstract*— This paper presents a template-based approach to detect objects of interest from real images. We rely on AM-FM models and specifically, on the Dominant Component Analysis (DCA) for feature extraction. We incorporate the results from AM-FM models for object detection. In order to detect the object of interest from real images patches are introduced. In order to find the degree of match between the patch and template, the AM-FM features are calculated. To find the correlation between the template and image patch, mean and standard deviation of image patch and template are calculated. If this correlation value exceeds a preset detection threshold, we declare that patch contains the object of interest. The combination of AM-FM features and template based object detection produces efficacious results.**

Keywords- AM-FM models, demodulation, object detection, template matching.

I. INTRODUCTION

The detection of objects in images is a central research topic in image processing and computer vision. Object detection deals with detecting instances of semantic objects of a class in images and videos. One of the most fundamental means of object detection with in an image is by template matching, in which a replica of an object of interest is compared to all unknown objects in the image [6], [7]. If the template match between an unknown object and the template is sufficiently close, the unknown object is labeled as a template object. Template matching is a technique in digital image processing for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot or as a way to detect objects in images [7]. In operation, the template is sequentially scanned over the image field and the common region between the template and image field is compared for similarity. A template match is rarely ever exact because of image noise, spatial and amplitude quantization effects. In case of localizing the object given as a template in the image the problem reduces to simple searching.

This paper is organized as follows. Section (2) briefly describes AM-FM image models and Dominant Component Analysis (DCA). In section (3) we introduced our approach for detecting the object of interest in a given target image. In section (4) we present our experimental results. Finally section (5) presents conclusion.

II. RELATED WORK

2. AM-FM IMAGE MODELS

AM-FM models analyze an image in terms of spatially varying amplitude and frequency modulated sinusoids [1], [2], [3]. AM-FM functions are non stationary quasi-sinusoidal oscillations that admit simultaneous amplitude and frequency modulations. A general 2-D AM-FM function takes the form

$$f(x, y) = a(x, y) \exp[j\phi(x, y)] \text{.........} (1)$$

where *a(x, y)* is the *amplitude modulation function,* or *AM function* of *f(x, y)* and $\nabla\ \Phi(x, y)$ is the *frequency modulation function* or *FM function* of *f(x, y).* The Amplitude Modulation function *a(x, y)* captures the local contrast of the complex valued image *f(x, y),* while the Frequency Modulation function $\nabla\ \Phi(x, y)$ captures the local image structure (orientation and granularity). The instantaneous frequency vector may be further decomposed into an instantaneous horizontal frequency function $U(x, y) = [1\ 0]\ \nabla\ \Phi(x, y)$ and instantaneous vertical frequency function $V(x, y) = [0\ 1]\ \nabla\ \Phi(x, y)$.

Even though many natural textures can be modeled in terms of a monocomponent AM-FM signals, images with 2D structure containing patterns like corners, crosses, and junctions necessitate that more than one component be simultaneously present in the local image spectrum [1], [2].The multicomponent AM-FM model models an image I as the superposition of locally narrowband sinusoidal components $f_k(x, y)$

$$I(x, y) = \sum_{k=1}^{K} a_k(x, y) \exp[j\phi_k(x, y)] \text{ ......} (2)$$

The fundamental problem of image demodulation aims at estimating, for each K components, the instantaneous amplitudes and frequencies. The decomposition of an image in terms of this expression is an ill-posed problem due to the existence of infinity of modulating signal pairs and component superposition satisfying (2). The demodulation algorithm suffers from cross-component interference. Hence it is necessary to separate the individual components from one another.

One popular strategy for isolating the multiple image components in (2) is to apply a multiband Gabor filter bank as described in [2]. Appropriate modifications to the demodulation algorithm and its discrete counterpart are discussed in [2] such that the modified algorithm can be applied directly to the filter bank channel responses to simultaneously estimate the multiple AM and FM functions $a_k(x, y)$ and $\phi_k(x, y)$ in (2). It then becomes possible to extract the dominant modulations on a point wise basis. This approach is known as *Dominant Component Analysis*, or DCA.

2.1 DOMINANT COMPONENT ANALYSIS (DCA)

In this section we describe an analysis technique known as Dominant Component Analysis (DCA) which, for an image of the form (2), will estimate the quantities $\nabla\phi(x)$ and a(x) of the locally dominant component [1], [5]. DCA offers a rigorous and compact way for capturing locally emerging modulation signals. A compact texture description can be extracted using the DCA methods, which retain the most prominent structure of the textured signal [5]. The Dominant Component Analysis technique finds the dominant modulations at each pixel giving a modulation domain representation for an image. Such models have been used successfully in several applications including texture-based segmentation, fingerprint classification, content based image retrieval and template tracking [5]. A block diagram of the approach is shown in the Fig. 1, where the image f(x) is analyzed with an M-channel multiband bank of Gabor filters. The filtered demodulation algorithm is applied to the responses of each channel at each pixel.

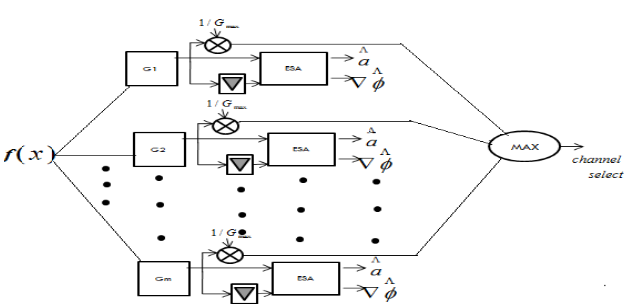

Fig. 1. Block diagram of the dominant component technique.

The Dominant Component Analysis scheme, chooses the most powerful of these channels at each pixel and estimates the AM-FM model parameters at that point using the outputs of that channel. This way, the output of the filtered image is combined, resulting in a low dimensional texture descriptor.

III. TEMPLATE BASED OBJECT DETECTION

AM-FM Demodulation

In this section an efficient scheme for the demodulation of the narrowband components into smooth modulating functions is summarized. Consider a single-component continuous domain image s(x, y), with associated analytic image f(x, y) = a(x, y) exp (j ϕ (x, y)). The AM and FM features are demodulated as

$$\mathbf{a(x, y) = |f(x, y)|}$$

$$u(x, y) = \nabla^x \varphi(x, y) = R\left[\frac{\nabla^x f(x, y)}{jf(x, y)}\right]$$

$$v(x, y) = \nabla^y \varphi(x, y) = R\left[\frac{\nabla^y f(x, y)}{jf(x, y)}\right]$$

$$R(x, y) = \sqrt{u^2(x, y) + v^2(x, y)}$$

$$\theta(x, y) = \arctan\left(\frac{v(x, y)}{u(x, y)}\right) \text{ .... } (3)$$

Where ∇^x and ∇^y denote partial derivatives along x and y, respectively.

TEMPLATE BASED OBJECT DETECTION

Template matching is one of the earliest and simple techniques which find known patterns in an image. In case of localizing the object given as a template in the image the problem reduces to simple searching. The rectangular matrix on which the pattern is defined is referred as mask or template. The idea of template based object detection, here, is to place the patches at all possible pixel locations of the image and compare the content of each patch and the template. This means the problem is to compute the degree of match between the each patch and template.

In this section, a template based object detection method using dominant AM-FM features is introduced. The aim of this method is to detect whether the object of interest is present in a target image or not.

The template is rectangular with known width *w* and height *h* and is chosen to enclose the object of interest. In order to detect the object of interest patches with Parameter vector =**[r c** α ϕ **]** are introduced where (r, c) represents the position of centre of the patch, α denotes the scale and ϕ is the orientation of the patch with respect to the horizontal axis. The components r and c are taken uniformly distributed over the entire image. Component α is taken to be uniformly distributed with mean 1 and ϕ to be uniformly distributed with mean 0. We choose L candidate patches to detect the object of interest in a given target image.

Initially, the patch is of same size of the template, place the patch at all possible pixel locations of the target image. In order to find the degree of match between the imposed patch and template, first the AM-FM features of imposed patch and template are calculated by using (3) and in order to find the correlation between the imposed patch and template, mean and standard deviation of patch and template are calculated. Let { $f_{n,D}$; D $\in$ {a, R, θ }} denote the features of the nth wraped image patch. $f_{n,a}$ is a matrix containing the AM features of the nth candidate patch and $f_{n,R}$, $f_{n,\theta}$ are the two matrices of FM magnitude and orientation of the n[th] patch.

The detection criterion is the correlation between the features of the wraped image patches and features { b_D ; D $\in$ {a, R, θ }} of the template computed using (4)

$$\gamma_n = \sum_{D \in \{a, R, \theta\}} \left(\frac{\sum_{(j1,j2)\in W} (f_{n,D} - \bar{f}_{n,D})(b_D - \bar{b}_D)}{f_{n,D}^{sd} b_D^{sd}} \right) \quad \ldots..(4)$$

Where { $\bar{f}_{n,D}, \bar{b}_D$; D $\in$ {a, R, θ }} are the means and { $f_{n,D}^{sd}, b_D^{sd}$; D $\in$ {a, R, θ }} are the standard deviations of the image patch and template window of features, respectively. W represents a spatial width *w* and height *h* located at (r_n, c_n) . If γ_n exceeds a preset detection threshold; we declare the nth patch contains the object of interest. The flowchart of the proposed method is as shown in Fig. 2.

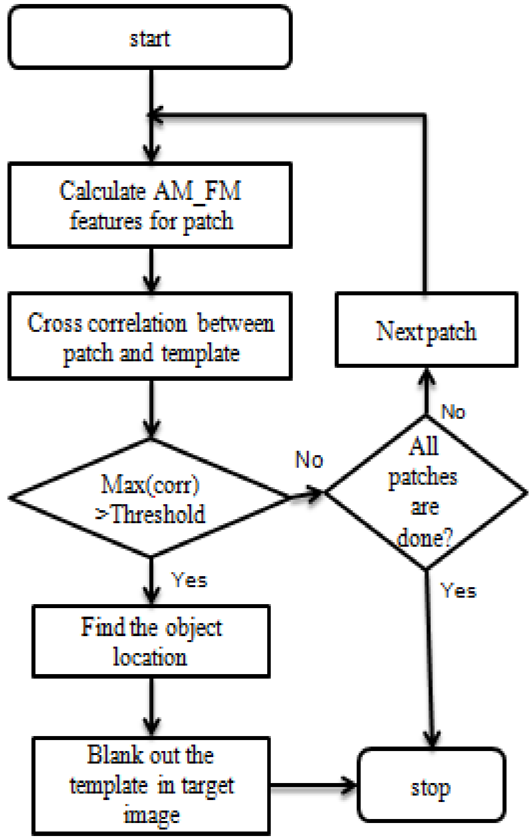

Fig. 2. Flowchart of Template based object detection.

IV. EXPERIMENTAL RESULTS

In this section we present experimental results with the proposed method. Target image and template are input to the proposed method. The aim of the proposed method is to find whether the template is present in the target image or not. In order to detect the object of interest patches are introduced, by placing these patches at all possible pixel locations the object is going to be detected. AM-FM features are calculated for each patch and template. In order to find the degree of match between the patch and template, mean and standard deviation of patch and template are calculated. The correlation is calculated between patch and template, if this value exceeds a preset detection threshold, then that patch contains object of interest.

Fig. 3(a), Fig. 4(a), Fig. 5(a) and Fig. 6(a) represents the input target image, Fig. 3(b), Fig. 4(b), Fig. 5(b) and Fig. 6(b) represents the template image and Fig. 3(c), Fig. 4(c), Fig. 5(c) and Fig. 6(c) shows output of the proposed method that detects the area of given template image in a given input target image. The experimental results shows that proposed approach is effective and feasible.

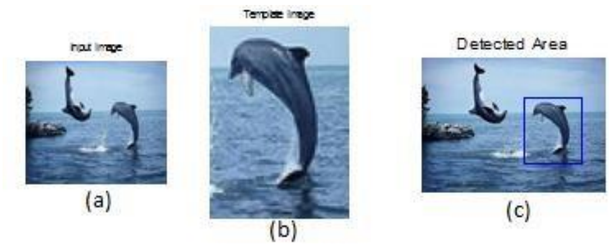

Fig. 3. (a) Target image (b) Template (c) Output of our method.

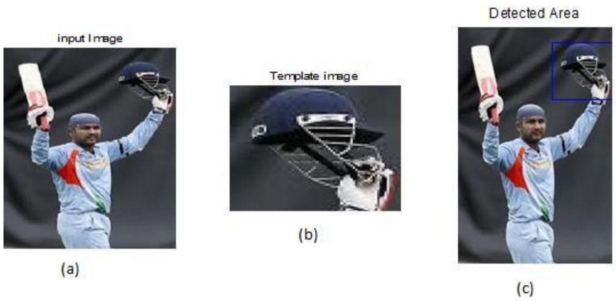

Fig. 4. (a) Target image (b) Template (c) Output of our method.

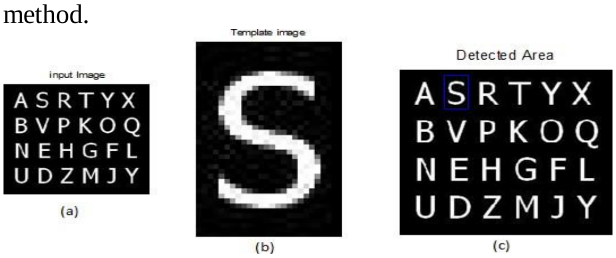

Fig. 5. (a) Target image (b) Template (c) Output of our method.

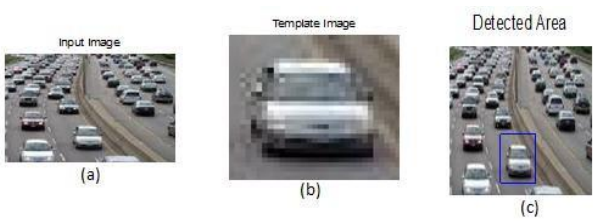

Fig. 6. (a) Target image (b) Template (c) Output of our method.

V. CONCLUSION

The multicomponent AM-FM representation is a powerful, important new emerging technique for modeling, analysis, and representation in a general image processing framework. In this paper, we first summarized the AM-FM models that analyze an image in terms of Amplitude Modulated (AM) and Frequency Modulated (FM) sinusoids. Dominant Component Analysis (DCA) that offers a rigorous and compact way for capturing locally emerging modulation signals. A compact texture description can be extracted using the DCA methods, which retain the most prominent structure of the textured signal. The dominant component analysis (DCA) technique finds the dominant modulations at each pixel giving a modulation domain representation for an image. We presented AM-FM demodulation and Template based object detection method and we have successfully applied our object detection method to various images.

In future work, we intended to explore the use of AM-FM/DCA models in object tracking as well as object recognition. The AM-FM/DCA models have not yet been brought to their full potential. The combination of model-based and feature-based approaches can serve as a reliable front end for higher level computer vision tasks.

VI. REFERENCES

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