Daily Clothes Observation from Visible Surfaces Based on Wrinkle and Cloth-Overlap Detection

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Abstract

This paper describes about a method of state observation of clothes. The method assumes to be applied as a visual function of daily assistive robots tidying up clothes in daily environment. A set of gabor filters are applied to an input image by changing its frequency and direction. Combination and selection of these parameters provide adequate information to know where wrinkles or cloth-overlap exist on a cloth. An algorithm from detection to observation is also proposed and verified through some experiments.

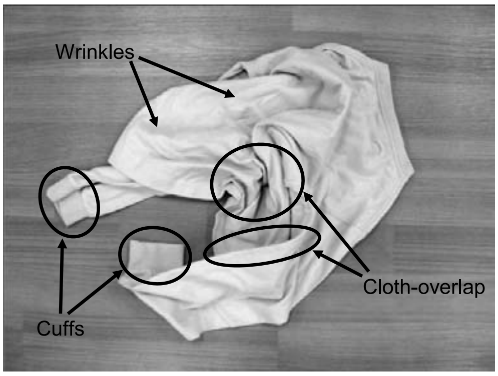

Figure 1. A clothes

1 Introducition

In daily environments various types of clothes exist for human lives. One of the effective daily assistances by robots will be achieved if the robots can manipulate the clothes because human often has many tedious housework on it. We aim to develop recognition modules for a daily assistive robot which can tidy up washed clothes like a housekeeper.

Comparing with approaches of recognition aimed at solid objects, soft objects such as clothes have significant difficulties because of its variable shape and appearance. Although recent image features provides highly reliable results in the purpose of object detection and pose estimation, they cannot be used in clothes. To attack the issues of clothes state observation, some researchers used image features which can be observed from clothes [4, 6]. In the viewpoint of robotics researches, vision application for cloth handling have been developed [2, 5]. However, as these results were mainly focused on robots which are emplaced, manipulation skills were more targeted under the condition of strictly constraints depending on environments or manipulation targets. On the other hand, daily assistive robots must do its tasks with moving around real environments. Therefore, finding clothes from the environment and observing it in more detail are also an important issue along with soft object manipulation and so on.

Yamazaki et al. [7] proposed feature representation based on wrinkles on a cloth, and used it to find clothes from daily scene. However, it will be insufficient for applying to tidying tasks by a robot because more additional analysis such as finding grasping point was not considered. The method proposed in this paper shows one of the approaches for understanding the state of a clothes by taking a notice of two types of features: wrinkle and cloth-overlap. Multi-scale and multi-orientation filtering are applied to an input image capturing a clothes, these features are extracted and analyzed.

The rest of this paper is organized as follows: next section how to detect wrinkle and cloth-overlap is explained. Section 3 introduces an algorithm which considers from cloth detection placed on daily environment and its state observation. Section 4 shows some experimental results, and section 5 concludes this paper.

2 Wrinkle and cloth-overlap detection

Figure.1 shows an example of a clothes readily placed on a floor. This is a shirt with long sleeves, which material is cotton. We can divide this clothes into some parts: (i) cuffs or other specific parts, (ii) wrinkles and (iii) cloth-overlap. The information of (i) tells us what kind of clothes it is. On the other hand, (ii) and (iii) may provide us with useful information for handling it, for instance, it gives grasping point for folding up. When we consider to develop a daily assistive robot which can perform chores, these information of clothes is useful for planning the motion of the robot.

2.1 Outline

We focus on the fact that contrast of image region about clothes shows gradually changes on frequency domain. In other words, a clothes has strip-shaped states because of the soft body.

In order to analyze this property, a number of gabor filtering is applied to an input image. In the filtering, parameters of wave profile are variously changed, and then helpful information is extracted from the convolution results. For instance, high frequency coefficient often highlights contour and cloth-overlap. On the other hand, low frequency coefficient constantly responds to wrinkles.

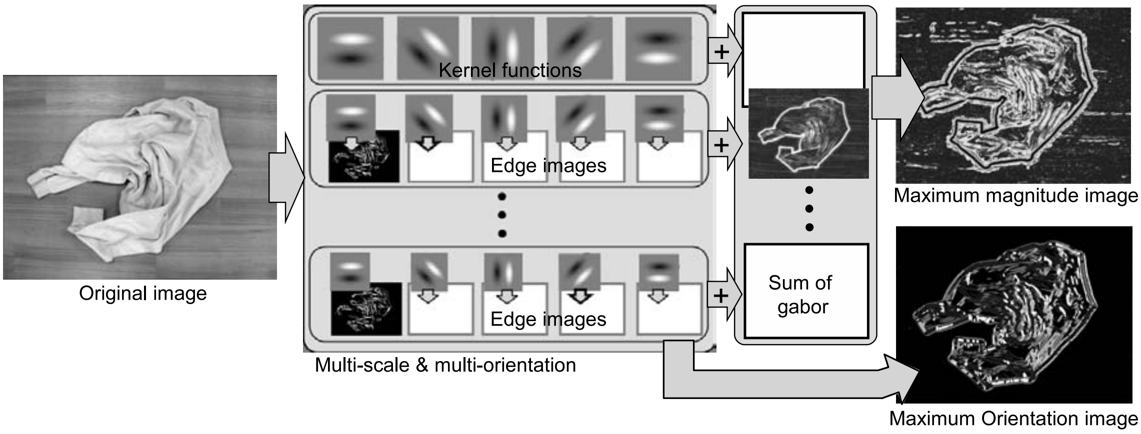

Figure 2. Multi-scale & multi-orientation filtering. In the maximum magnitude image, the brighter pixel indicates a pixel which reacts in the larger scale parameters. In the maximum orientation image, the difference of pixel radiance indicates the direction of each wrinkle region.

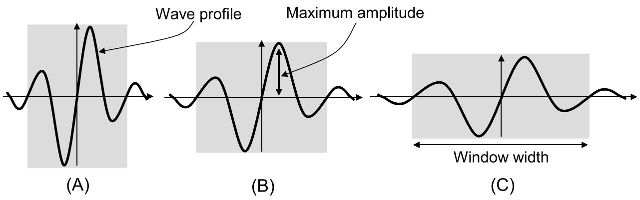

Figure 3. Wave profiles

Two types of intermediate images are generated. One is called "maximum magnitude image" in the rest of this paper. Each pixel in the image has a value related to a variance which provides maximum magnitude during scale space generation. Another is called "maximum orientation image". Each pixel in the image has a value related to an angle which indicates maximum reaction among gabor filtering about specific scale. Because latter image is used to find wrinkle region, large value is set to the scale parameter. Combining these two images, we are able to extract various information of the target clothes.

Figure.2 shows the concept of filtering. Various kernel functions of gabor filter are prepared, and some results are integrated for generating two proposed images.

2.2 Gabor Filter

We apply gabor filter [8] to detect feasible information of clothes. 2-dimensional gabor filter is a filter in which direction and frequency can be arbitrary changed. It has often been applied to scale space analysis. The equation is as follows:

$$g(\mathbf{x}, \theta, \sigma_x, \sigma_y) = \frac{1}{\sqrt{2\pi}\sigma_x\sigma_y} e^a \cos(2\pi f x_\theta + p), \quad (1)$$

where

$$\begin{aligned} a =& \quad -\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right), \\ x_\theta =& \quad (x - u_x)\cos\theta + (y - u_y)\sin\theta, \\ y_\theta =& \quad -(x - u_x)\sin\theta + (y - u_y)\cos\theta. \end{aligned} \quad (2)$$

The f is frequency domain. In our case, this value depends on variance value σ. As shown in Figure.3, the f forms a wave in a stated range which is defined by σ. x and y are coordinates of present pixel, u_x and u_y are center coordinates of gaussian distribution. σ_x^2 and σ_y^2 are variance, both of them are represented as σ in the rest of this paper. So, $f(\mathbf{x}, \theta, \sigma_x, \sigma_y)$ is represented as $f(\mathbf{x}, \theta, \sigma)$. p is a variable of phase, and we substitute $\pi/2$ in it because edge detector should be generated in our case.

2.3 Multi-scale and multi-orientation filtering

As pre-processing to generate a maximum magnitude image and a maximum orientation image, gabor filters are applied with constant σ and variable θ in eq. (1). Because a gabor filter has directionality, resulting images includes various edges relying on the θ setting.

A maximum orientation image $I_{ori}(\mathbf{x})$ is generated from these results. A pixel information is written as follows:

$$I_{ori}(\mathbf{x}) = argmax F_1(\mathbf{x}, \theta), \quad (3)$$

where $\mathbf{x}$ denotes pixel coordinates and θ denotes the inclination angle of a kernel function in equation (2). The $F_1(\cdot)$ is a continuous function concerning θ and neighbor pixels.

$$F_1(\mathbf{x}, \theta) = \int_w f(\mathbf{x}) g(\mathbf{x} + \mathbf{x}_0, \theta) d\mathbf{x}_0, \quad (4)$$

where $f(\mathbf{x})$ indicates an input image and w denotes window size of the convolution. In this process, if filtered pixels indicate negative value, they are modified as 0.

In practice, $I_{ori}(\cdot)$ is calculated from discrete values $(\theta_1, \theta_2, \cdots, \theta_N)$ with $-\pi < \theta_n \leq \pi$ range. After the pre-processing with varying θ, an image is generated by collecting the highest radiance value at same pixel coordinates in the image set. In the case of clothes, ellipsoidal regions are represented along wrinkle directions.

On the other hand, for generating a maximum magnitude image, following procedure is needed. First, multi-orientation filtering mentioned above is performed, and then we get an image whose pixels are the sum of the result of gabor filtering with varying θ. (In Figure.2, 'Sum of gabor' indicates it.) We call the image 'temporal image' in the rest of this section.

By varying σ, a set of temporal images is generated. Maximum magnitude image consists of pixels which indicate maximum radiance in the temporal images. Now we define a pixel of maximum magnitude image $I_{mag}(\mathbf{x})$. It can be written as follows:

$$I_{mag}(\mathbf{x}) = argmax F_2(\mathbf{x}, \sigma), \tag{5}$$

where

$$F_2(\mathbf{x}, \sigma) = \int_{\theta} \int_{w} f(\mathbf{x}) g(\mathbf{x} + \mathbf{x}_0, \theta, \sigma) d\mathbf{x}_0 \mathbf{d}\theta. \tag{6}$$

Window width w and frequency f are decided from σ value automatically. In our implementation, the window width was set as $w = 6 \times \sigma$ and the frequency was set as $f = 1/(3 \times \sigma)$. Meanwhile, maximum amplitude of wave function is obeying following equation:

$$\lambda_{max} = \frac{cons}{x}. \tag{7}$$

In our case, the *cons* value became 0.3171.

3 An algorithm for clothes detection and observation

In this section, we proposed an algorithm for cloth observation as an application to daily assistive robots.

3.1 Image segmentation for clothes detection

If it is assumed that clothes are randomly placed on daily environment, what we first to do is to find target clothes. In our case, image segmentation technique is applied.

In general, a home environment consists of floor, wall, ceiling and furniture. Because less texture can be observed from almost of them, synergetic image segmentation is suitable to detect candidate spots where clothes are. Mean-shift base segmentation [1] in which the image pixels are clustered with delineating a homogenous region at color space is applied from the reason. As intermediate results, region adjacency graph and edge information are generated. Since for pixels close to an edge is weighted with small value, this helps the result of mean shift. To integrate the discontinuity, for each edge in the region adjacency graph is computed by averaging pixels values on the boundary shared by two regions.

3.2 Wrinkle and cloth-overlap detection

After the image segmentation, actual clothes region should be selected. For instance, a cloth detection method based on wrinkle feature [7] can be applied to identify the region of clothes in an image.

As most of daily assistive robots will have mobile base, it is able to approach to the specified clothes. After that, the process described in section 2 should be applied. Applications providing necessary information such as clothes categories or grasping points will be expected from the results.

Figure 4. Examples of clothes image dataset

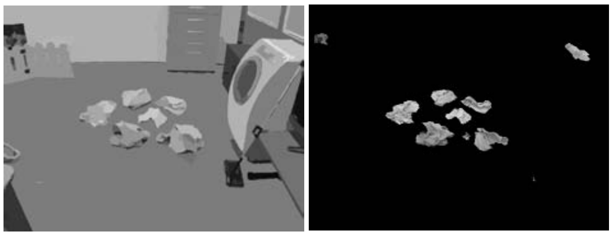

Figure 5. A segmentation result. An input image is shown in upper left in Figure.4. Left: a result of mean-shift based segmentation, right: wrinkle feature based clothes detection

3.3 Target clothes observation

The procedure described in section 2.3 is relatively simple but useful for knowing the clothes state. If convolution is performed on boundary part, I_{mag} often comes out of filtered image with small σ. On the other hand, intermediate σ produces constant reaction on wrinkle region.

From these facts, we divide clothes region into 2 remarkable and 1 other regions; (i) wrinkles (L_{wkl}) , (ii) boundary and cloth-overlap (L_{bco}) , (iii) smooth region (L_{smo}). These likelihoods are calculated obeying below equations:

$$L_{wkl} = p_{wm}(\sigma) I_{mag}(\mathbf{x}),$$

$$L_{bco} = max(p_{bm1}(\sigma) I_{mag}(\mathbf{x}), p_{bm2}(\sigma) I_{mag}(\mathbf{x})), \tag{8}$$

where $p_{*m}(\cdot)$ indicates probabilistic function. we set a normalized distribution.

The average of $p_{wm}(\cdot)$ is located with large σ, and precipitous distribution is assumed. On the other hand, two distributions are set to calculate L_{bco} because there are two peaks to find cloth-overlap in both small σ and large σ. If both L_{wkl} and L_{bco} are small, L_{smo} becomes large.

4 Experiments

4.1 Setting

Over 60 images which captured clothes existing daily environments were prepared. As shown in Figure.4, several type of clothes such as cotton shirts, parka and white shirts were selected as daily clothes, and they were placed on randomly.

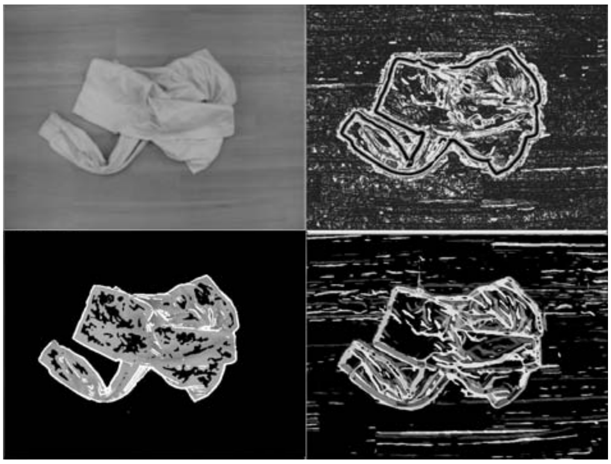

Figure 6. An intermediate result of cloth state observation. Upper left: original image, upper right: maximum magnitude image, lower right: maximum orientation image and lower left: detection result of cloth-overlap and clothes boundary (with white lines)

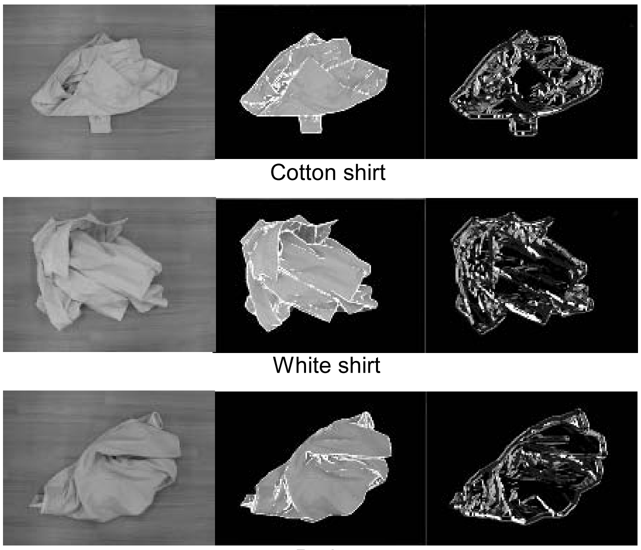

Figure 7. Experimental results. Right figures show maximum orientation images. The difference of radiance indicates direction of wrinkles.

4.2 Experimental results

Figure.5 shows one of clothes detection results. By using mean-shift based segmentation, all of floor region is segmented as one region. After that, clothes are individually detected by using wrinkle feature.

Figure.6 shows intermediate results on clothes observation. Upper right shows a maximum magnitude image. In this image, black pixels derive from small σ, and if the radiance higher, it derive from large σ. Boundary between clothes and floor could be detected by black edges, and cloth-overlap could be found as bright regions. From these results, we will able to see daylight to develop other robotic manipulation functions to decide grasping point. One feasible way is to select grasping points on cloth-overlap considering the direction of pulling up for getting rid of more amount of wrinkles.

Figure.7 shows some other experimental results. Images in right column shows the results of extracting maximum orientation. Ellipsoidal regions as the elements of wrinkles could be found from them, the number of the regions were 245, 275 and 233 respectively. These information will be able to be used for designing a descriptor which represents the state of a cloth. In these experiments, the range of varing σ was from 1.0 to 8.0 at 1.0 intervals. Average value in probabilistic function of $p_{wm}(\cdot)$, $p_{bm1}(\cdot)$ and $p_{bm1}(\cdot)$ in eq.(8) were set as $\sigma = 4.0$, $\sigma = 2.0$ and $\sigma = 6.0$ respectively.

5 Conclusion

In this paper we proposed a state observation method for clothes which are readily placed on daily environment. A set of gabor filters are applied to an input image with changing its frequency and direction, and useful information such as wrinkles and cloth-overlap are detected based on maximum magnitude and orientation. The detection method is combined with image segmentation techniques, an algorithm for finding clothes was also presented. Experiments show the effectiveness of our method.

Future work, more feasible information to know the state of clothes should be added. After that, we will try to develop a method which enables a daily assistive robot to handle daily clothes.

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