

Estimation of Coefficient of Static Friction of Surface by Analyzing Photo Images

Hitoshi Tamura and Yasushi Kambayashi

Abstract We propose a method to estimate the coefficient of static friction of floor surfaces by analyzing photo image of the floor tiles. The image features that we use to estimate the coefficient are micro-shape features and micro-depth features. We extract the difference between the flash images and the non-flash images of floor tiles. We have composed an equation by applying multiple linear regression analysis that sets the image features as explanatory variables and the measurements of the tile images as objective values. As the result, we have obtained an estimate equation that coefficient of determination R^2 is 0.97 and we observed the two-sided 95 % confidence interval ± 0.053 . We can say that the equation is good enough for practical use.

Keywords Coefficient of static friction • Texture analysis • Image measurements • Shape-pass filter • Micro shape feature • Micro depth feature

1 Introduction

Coefficient of static friction of a floor is an important factor for controlling a robot. It is difficult to measure the friction coefficient without contacting the floor. Watanabe et al. proposed a control method for the grasping device that doesn't use the friction coefficient [1]. If we can estimate the coefficient of the floor in front of a robot only though image sensors, we can increase the stability of controlling robots. In this paper, we propose a method to estimate coefficient of static friction of a floor

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tiles by analyzing two photo images of the floor tiles. We are not aware of many researches for measuring frictional properties by only through visual information. Even though Kim et al. proposed a method for classifying terrains and for predicting friction coefficient on terrains by applying visual information, their method doesn't measure frictional properties directly [2].

Authors have treated a photo image of the floor tile as a random texture image and have applied general-purpose texture analysis filters, which are called shape-pass filters, to the texture [3, 4]. The shape-pass filters are nonlinear filter banks that extract micro-shape features from the random texture image.

We set an assumption that image features have a correlation with frictional properties. Image features we are using are the micro-shape features and the micro-depth features on a surface. We have composed an equation to estimate the coefficient of static friction of the floor tiles by applying multiple linear regression analysis that set micro-shape features and reflection features as explanatory variables.

The structure of the balance of this paper is follows. In Sect. 2, we explain both the micro-shape features and the micro-depth features. In Sect. 3, we compose the estimate equation from the sample images and friction data. We then confirm our equation through discriminant analysis and estimation of the coefficient of friction in Sect. 4. In Sect. 5, we examine the frictions according to the directions. Finally we conclude our discussion in Sect. 6.

2 Features in Images

2.1 *Micro Shape Features*

Research scientists have proposed various approaches for texture analyses [5–9]. In our method, we interpret a texture as a collection of tiny elementary shapes and classify the texture images by analyzing which portions in the texture image contain certain elementary shapes. We extract these shapes by applying nonlinear procedures that use only local pixels in the given texture image. When we scan the entire image, we use one local domain as a window and apply the nonlinear procedures to each local domain as the filtered area. Each local domain corresponds to a point spread area for a linear image filtering.

There is no widely accepted standard that defines what shapes are elementary for characterizing textures. The authors propose the five shapes, namely black-line, black-pepper, black-roof, black-snake, and cliff as the elementary micro-shape features as shown in Fig. 1. Both the line and the snake consist of one thin black area but the latter is curved. The pepper consists of an isolated small black area. The roof is characterized as containing a black area fanning from the center of a specified small area in some angle narrower than 90° . The last one represents about fifty-fifty partition of black and white area. Since a negative photograph of a general

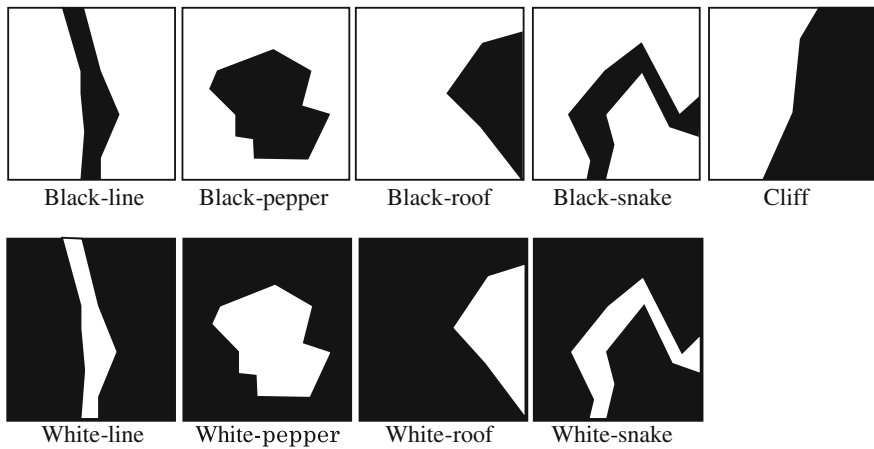


Fig. 1 Micro-shape features

texture from positive one can be recognized as different features, we also introduce four shapes in which black and white areas are reversed as shown in Fig. 1. Thus we set the black roof, the black line, the black snake, the black pepper, the white roof, the white line, the white snake, the white pepper, and the cliff are the elementary shapes.

We do not employ the traditional simple pattern matching to extract the micro shapes. Instead, we nonlinearly extract the micro shapes by applying well-defined procedures. We define one extract procedure for each micro-shape. In the procedures, we classify the pixels in the filter area into two values, and then we determine the shape of the black pixels that exists at the center of the local domain. For example, the procedure for the black pepper detects the existence of a small black isolated area.

The filtering procedure determines the value at the center of the local domain as the output value of the area. The output value is not simple black-and-white value obtained from the filtered area but the average of brightness of the original image of the area. The filtering procedure scans the entire image and produces the output value of each position of the image. Figure 2 shows an example. The left figure is the original input image, and the right figure is the output image obtained by applying the black-roof filter procedure to the input image. The white dots in the output image are not just white but gray scaled.

Output images of the filter contain features of shapes. The representing value of the output images is RMS (root mean square value) of the output image rather than a simple average value. Only brightness information on each pixel is used here because the procedure pays attention about the shape features. The filtering procedure does not use any information on colors, such as Chroma.

The size of the local domain affects to determine the shape feature of the given filter area. Therefore, we extract each micro shape feature by five sizes of the filter

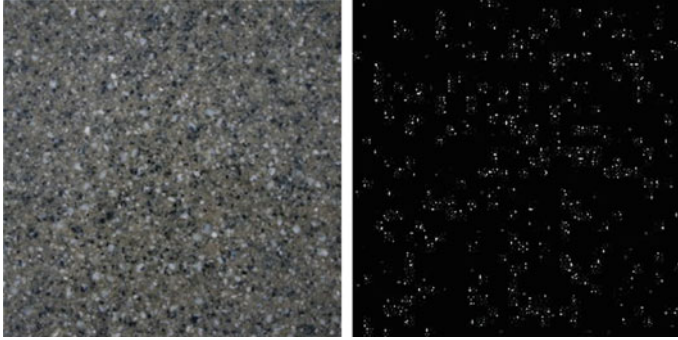


Fig. 2 Example of an output image of the Black-roof filter (*right*) and an input image (*left*)

area: 5×5 , 7×7 , 11×11 , 15×15 , and 21×21 pixels. In other words, we apply the procedures to forty-five features, i.e. nine shapes \times five sizes, and stream into the regression analysis to obtain the estimation equation.

2.2 *Micro-Depth Features*

In addition to the micro shape features, we use the micro-depth features for estimation. The micro depth features are characterized by existence micro unevenness on the surface. The features are obtained by observing the difference between the flash images and the non-flash images. The flash image is an image that is taken with flash, and the non-flash image is an image that is taken without flash. When the examined area is uneven, the flash produces some shadows. Thus we can measure the micro-depth by examining the difference between the flash image and the non-flash image as shown in Fig. 3.

We prepare the two images; the flash image and the non-flash image for each of forty-five micro shape features that are obtained from one floor tile. We also obtain forty-five micro depth features by taking the difference between the flash images and the non-flash images. Therefore we obtain in total 135 ($= 45 + 45 + 45$) features for one floor tile. When obtaining images of a floor tile, using the flash affects the determination of the micro shape features greatly, especially when there is a small ruggedness on the surface of the floor tile. It is clear that the ruggedness on the surface influences frictional properties. The reason why we extract the micro shape features from not only non-flash images but also flash images is to detect this micro ruggedness on the surface by taking the difference between the micro shape features in the flash and the non-flash images. A part of these features are selected for estimation of coefficient of static friction of the floor tile surface by applying the multiple linear regression analysis to the sample images.

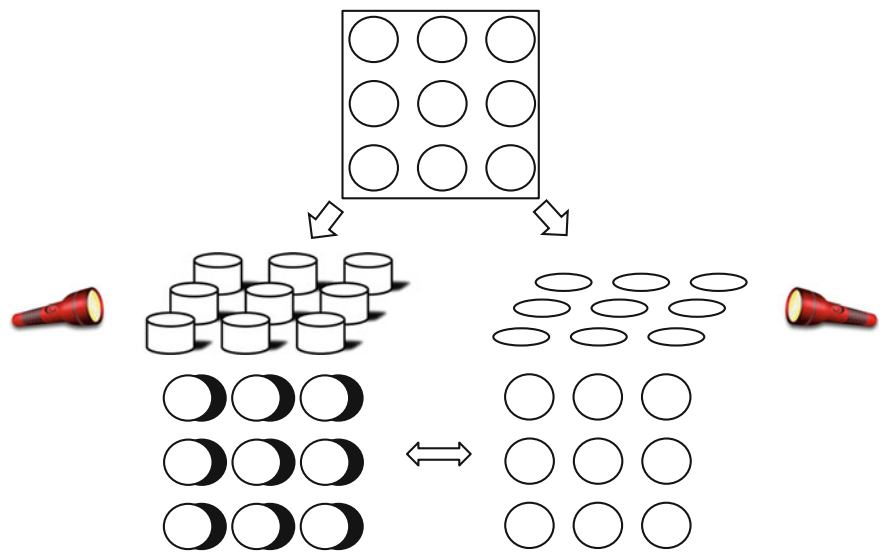


Fig. 3 Micro depth feature can be extracted by examining the shadow produced by unevenness

3 Composing Estimate Equation

3.1 Sample Images

We have selected twelve samples of the floor tiles we have found on our campus. They are several kinds of linoleums, stone materials, wood surfaces, fiber carpets and concrete. Figure 4 shows them. We use those twelve samples for the analysis and experiments. We have taken forty pairs (flash and non-flash) of images for each sample tile; therefore we prepare 480 pairs of images in total.

Fig. 4 Twelve sample images

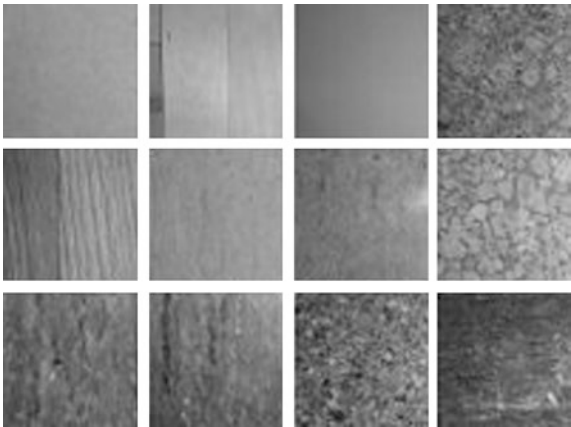
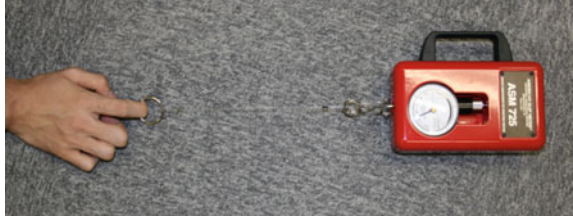


Fig. 5 Measuring coefficient of static friction



These are uniform and non-directional images. At this stage we ignore the directional factors to estimate the coefficient of static frictions. We assume the frictions are the same in all directions. We have setup a digital camera on tripod, and taken a picture of the floor tile of almost right under with the camera. We took a flash picture and a non-flash picture for one floor tile at the same condition.

Immediately after taking pictures, we have measured the frictional property of the floor tile with ASM 725 which is made by American Slip Meter that as shown in Fig. 5. We have measured the property of a tile ten times, and have recorded the measurement value for the tile is mean value of ten observed values.

We have employed 240 pairs of images among 480 pair of sample images for composing the estimate equation, and we have used the other half of the images for evaluation of the equation. We have composed the equation by applying the multiple linear regression analysis that sets both the micro-shape features and the micro depth features of the tile image as explanatory variables and the measurement of the tile image as objective value. We have performed the analysis by using the forward selection method that set 2.0 to F-in value and that set 2.0 to F-out value. Selecting those values in the restricted range D , we have composed the following polynomial equation, where a is the partial regression coefficient, x is the explanatory variable.

$$f = \sum_{i \in D} a_i x_i \quad (1)$$

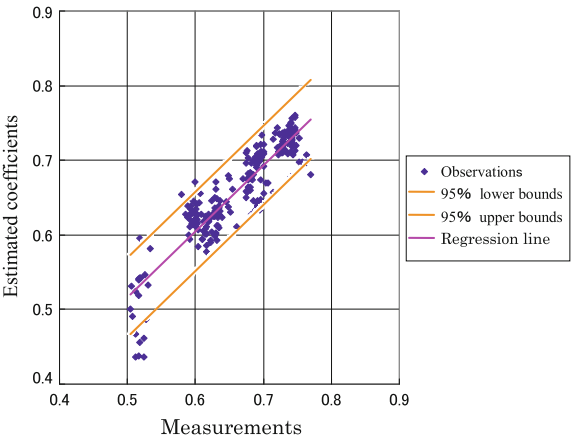
As the results of the multiple linear regression analysis, we have obtained the partial regression coefficient and explanatory variables. The results are shows in Table 1, where (depth) is the micro-depth feature. In Table 1, we set the explanatory variables in the descending order of the F values.

Figure 6 shows the results of the comparison. We can observe that the multiple correlation coefficient R is 0.90, and the two-sided 95 % confidence interval is ± 0.053 . The difference of 0.05 in frictional properties makes the maximum static friction power change by 5 %. This accuracy is good enough for practical use.

Table 1 Result of the multiple linear regression analysis

Explanatory var.	Partial regression coefficient	F value
Black-line 5 × 5 (depth)	−0.043	86.43
Black-line 5 × 5	0.043	82.33
Cliff 11 × 11	−0.010	67.14
White-line 15 × 5	0.064	52.58
Black-line 21 × 21	−0.010	48.14
Black-line 7 × 7	−0.041	46.43
White-line 5 × 5	−0.149	46.23
White-snake 21 × 21 (depth)	0.018	45.24
White-roof 21 × 21	0.014	38.76
Black-line 15 × 15	0.021	38.22
Black-snake 7 × 7	0.036	28.98
White-roof 15 × 15	0.013	28.83
Black-roof 15 × 15	0.011	25.75
White-line 5 × 5 (depth)	−0.075	25.36
White-roof 21 × 21 (depth)	0.007	23.25
Black-pepper 5 × 5	−0.064	22.68
Black-pepper 7 × 7	0.037	19.66
...
Constant	0.704	—

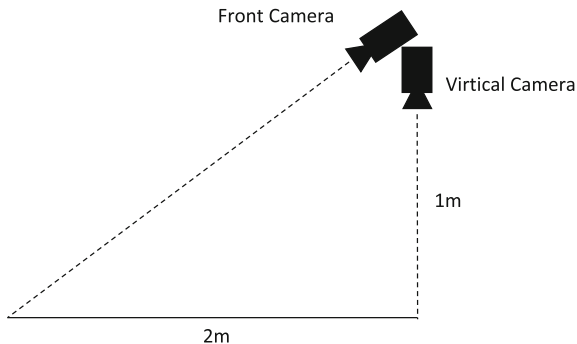
Fig. 6 Scatter diagram plotted the estimation values and the observation values the coefficients



4 Discriminant Analysis of the Floor Surface

As described in the previous section, we have confirmed that the estimation of the coefficient of friction using the images of the floor that are taken in vertical angle is quite precise. In order to apply this method to robotics, however, we need to extend

Fig. 7 Setting of the front camera and the vertical camera



the method so that it can use the images of the floor surface obtained by a camera in front of the robot.

The method we examined in the previous section depends on the uniform-density of the micro shapes in the picture of surface taken in vertical angle. The images taken by a camera in front of the robot cannot be uniform-density, because the camera captures distant shapes smaller and interprets them denser than the near shapes.

Since we can make accurate estimates with the images taken by the vertical camera, if we can determine the materials of the floor in front of the robot, we can estimate the friction of the floor in front of the robot. Therefore, we can compare the front image of the floor tile and the vertical images of the twelve kinds of floor materials in order to identify the floor materials in front of the robot by applying the discriminant analysis.

For the new set of sample pictures, we have taken pictures of the floor surfaces with a vertically set camera and pictures of the same surfaces with another camera set in low angle. The low angled camera is set about 30 cm high from the floor and focused 1 and 2 m ahead as shown in Fig. 7. We have taken fifty-four pictures in each distance of five places, and composed the estimate equation by the discriminant analysis at each place. The form of the equation is the same as (1). The only difference is the partial regression coefficients.

The discriminant analysis uses 45 of micro shape features ($9 \text{ shapes} \times 5 \text{ sizes}$). Since the lighting cannot be set up for front pictures, we have not used micro depth features.

As the result of discriminant analysis of the pictures of five places, we have observed that the distinction rates are 54–85 %. The particularly inaccurate place is a large tile block, and we found a crevice between tiles influenced aggravation of accuracy greatly. The results from the other places, however, show that the accuracy is practically good enough.

5 Estimation of the Directional Coefficient of Friction

It is well known that the frictions are directionally different from each other even with the same floor materials. Therefore it is desirable that we can estimate the maximum coefficient friction and minimum coefficient friction and their directions.

We have obtained the Fourier power-spectrum pictures from the floor surface pictures, as shown in Fig. 8. Then we have computed the average brightness according to direction, and obtained the maximum direction of each floor materials. The obtained maximum direction is called the lengthwise direction and it is known that the length-wise direction produces the maximum coefficient friction.

Forty-five of micro shape features and forty-five of micro depth features, ninety features in total, are used for computing the estimated frictions. Here, the micro depth features are obtained from the difference of the pictures flashed along the direction of the maximum coefficient of friction and along the direction of the minimum coefficient of friction.

The number of the floor surfaces we have used for the experiment is twenty-three. Six pictures were taken at each place, 138 pictures in total.

We have conducted multiple linear regression analysis over the set of maximum measured values of frictions and minimum measured values of frictions as the objective variables.

The results of the regression analysis by using the estimate equation for maximum coefficient and the estimate equation for minimum coefficient are shown in Figs. 9 and 10, respectively.

The coefficient of determination shows 0.86 with the estimate equation for maximum coefficient, and 0.88 with the estimate equation for minimum coefficient.

Fig. 8 Fourier power spectrum

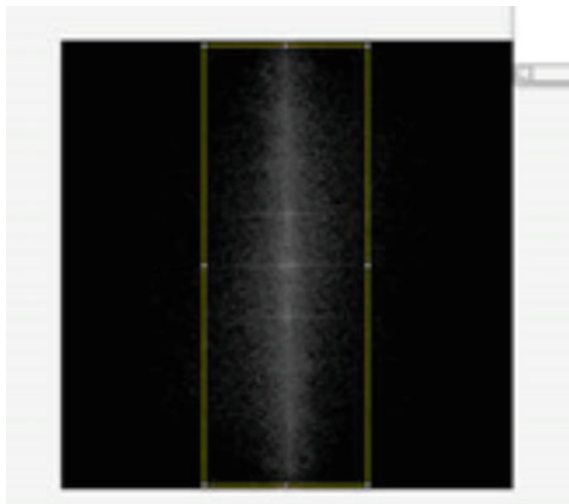


Fig. 9 Regression line for maximum coefficient of static friction

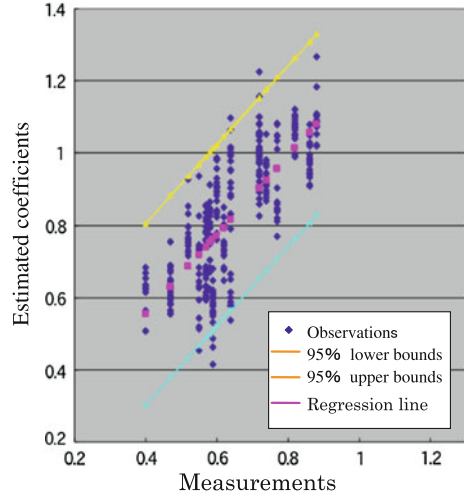
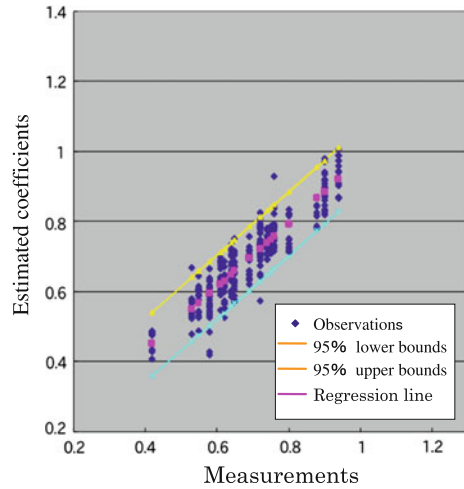


Fig. 10 Regression line for minimum coefficient of static friction



The results are not as good as shown in Fig. 6. The reason why the results are not so good may be that we did not use the smoother floor materials in the experiments. We can say, however, that at least the coefficient of friction has directional property.

6 Conclusion and Discussion

We have proposed a technique to estimate the surface coefficient of friction only using the surface images. We have extracted the micro shape features and the micro depth features from a uniform texture of the surface image and estimate the surface

coefficient of friction for each surface image. The proposed method consists of the following three functions.

1. The function that estimates the coefficient of frictions of the surface right below the camera with sufficient accuracy.
2. The function that identifies the floor material observed from the low angled camera.
3. The function that estimate the maximum and the minimum coefficients of friction with the pictures that have the directional property.

We have prepared forty-five micro shape features for each floor tile. Then, for each floor tile, we obtained two images; the flash image and the non-flash image. Also we have obtained forty-five micro depth features by taking the difference between the flash image and the non-flash image. In total, we obtained and used $135 (= 45 + 45 + 45)$ features in the floor tile for applying the multiple regression analysis.

We have observed the following results. Multiple correlation coefficient R is 0.90, and the two-sided 95 % confidence interval was ± 0.053 for the first function. Although the second function makes misjudgments for some materials, it can distinguish the floor materials with practically enough accuracy. The third function shows that the maximum and the minimum coefficients of frictions can be estimated from pictures with directions.

For the computational complexity, we use the least squares regression with N training examples and C features, and $N > C$. We can say that the computational complexity of matrix multiplications is $O(C^2N)$, and it is not significant in our setting: $C = 135$ and $N = 240$. Thus the estimation of the frictions can be performed by a notebook computer on a small mobile robot.

We are planning to integrate this algorithm into the control software for the electric wheelchair we are developing [10]. Successful inclusion of the algorithm should prove the usability of our algorithm in real-time setting.

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