Extraction of Dynamics-correlated Factors from Image Features in Pushing Motion of a Mobile Robot

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Abstract: It is important for autonomous robots to improve capability of extracting information that is relevant to their motions. This paper presents an extraction and estimation of factors that affect behavior of object from image features in object pushing manipulation by a two-wheeled robot. Motions of image features (SIFT keypoints) are approximated with variance. By detecting correlation between the variance and positions of the keypoints, the robot can detect keypoints whose positions affect behaviour of some keypoints. Position information of the keypoints is expected to be useful for the robot to decide its pushing motion. The proposed scheme was verified in experiment with a camera-mounted mobile robot which has no pre-defined knowledge about its environment.

1 INTRODUCTION

In recent years, autonomous robots are expected to act in more various environment, ranging from household to disaster site, outdoor, and so on. In such kinds of environment, many unknown factors will prevent the robots from accomplishing their tasks. For example, in a situation where a robot is needed to move an unknown object, it is very difficult to give preprogrammed plan to the robot about where to push the object with which direction because its motion depends on various factors such as shape, weight, stiffness, inertia and so on.

Immediate solution for this problem is to once avoid pursuing autonomy and apply human-controlled robots, but another approach can be to develop learning ability of autonomous robots to build recognition and motion-planning strategy by their own. Developmental robotics (Asada et al., 2009) is closely related to the above-mentioned approach since it aims to build not only motion learning ability (using reinforcement learning (Sutton and Barto, 1998) for example) but also recognition of environment while considering connection between recognition and robot's motion (Metta and Fitzpatrick, 2003).

As an example of recognition of environment, let's consider a case where a robot is going to manipulate an object. It will be important to know whether the robot can be push it, how it moves when the robot manipulates it, and what kind of factor causes its behavior. Developmental robotics deals with acquisition of such kind of information through leaning.

Madokoro *et al*. proposed recognizing and identifying an object by using visual sensor (Madokoro et al., 2012). After unsupervised learning using images collected in advance, robot recognizes the object using camera information. Nakamura *et al*. proposed a multi-modal object categorization by pLSA (probabilistic Semantic Analysis) and LDA (Latent Dirichlet Allocation), that are applied to information obtained when robot manipulates objects (Nakamura et al., 2007). In this research, robot grasps objects and observes them from various angles and it classifies object and estimate behavior of a new object. Nishide *et al*. proposed motion generation of object manipulation by applying a neural network to obtain information when robot manipulates object (Nishide et al., 2008).

In the researches mentioned above (Nakamura et al., 2007) (Nishide et al., 2008), how the robot should behave was given by human designers. But in order to construct ability of behavior generation, it is desirable to let the robot plan its behavior based on its trial and error instead of giving the robot motion information (time series of joint angle, for example). Another common problem for the related researches (Madokoro et al., 2012) (Nakamura et al., 2007) (Nishide et al., 2008) is that extraction of important factors that are influential to the robot's interest is made only as a result of a large-scale learning process, sometimes almost as a black box. For flexible motion generation, it is important to extract partial

dependencies between sensor observation. Therefore, construction of recognition based on robot's simple and elemental behaviors in a manner where relations among factors of sensor information are tractable, has not been realized yet.

This paper presents a method of extracting correlation between features obtained by sensor information based on elementary behavior of robot. Pushing motion of a mobile robot is considered as a task. In the process of pushing motion, image features that are relevant to changes of object behavior are extracted.

The remainder of the paper is constructed as follows. Problem settings are described in Section 2. Extraction of factors related to dynamics of observation is described in Section 3. Experiment is explained in Section 4, followed by conclusion conducted with a mobile robot.

2 PROBLEM SETTING

The experimental settings are depicted in Fig.1(a) and Fig.1(b). A mobile robot equipped with a camera (Fig.1(a)) moves on the floor while sometimes touching an object that is randomly located in its environment. The object will move according to the motion of the robot when they are contacting with each other. Examples of images captured by its camera are depicted in Fig.2, where part of the object is viewed in the image when robot is closely located to the object or is contacting with it.

It is assumed that size, shape, appearance of the object and as well as appearance of background are unknown to the robot. An implicit assumption for the object is that the object provides more than several SIFT (Scale Invariant Feature Transform) (Lowe, 2004) keypoints so that motion of the object can be detected by the keypoints corresponding to the object.

Control input given to the robot is desired velocities of the both wheels. Observation of the robot is images obtained at every frame. Both control and observation frames are one sec. Image features are obtained from each image as SIFT keypoints at a frame and correspondences with its preceding frame for each image are calculated by mean shift (Comaniciu et al., 2002). Mean shift algorithm is used to classify SIFT keypoints because feature value of SIFT keypoints changes gradually, and thus conventional SIFT matching algorithms do not work effectively. Process of classifying SIFT keypoints is depicted in Fig.3. Each keypoint extracted in an image has 128 dimension feature vector $\mathbf{V} = [v_1 \cdots v_{128}]$((1) in Fig.3). SIFT uses luminance gradient around keypoint for description of feature vector. SIFT divides

(a) Mobile robot with CCD camera. (b) Robot, object and environment

Figure 1: Problem settings.

area around keypoint to 16 area, and creates eight histogram of luminance gradient in every 45 degrees in each divided area. This 128 histograms are used as components of the feature vector. Mean shift is applied to $\mathbf{V}$. As a result, keypoints that have close feature vectors are classified into a common cluster((2) in Fig.3). Matching of the keypoints between two images is decided whether two keypoints belong to the same cluster((3) in Fig.3). Thus, not only position but displacement from its preceding frame is available as observation.

Finally, it is desirable that the robot system is to be able to plan how to approach to the object and push it when a target position of the object is given to the robot. For this goal, the robot first must be able to identify which part of image should be focused for the planning. In other words, the robot first needs to detect keypoints whose positions are influential to the behavior of the object. In this paper, we describe about extracting correlation between object behavior

(a) Robot at the center of object. (b) Robot at the right edge of object.

Figure 2: Examples of obtained image.

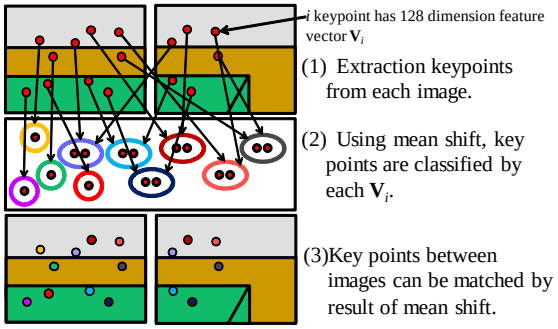


Figure 3: Process of classifying keypoints.

and position of keypoints in order to find keypoints that are useful for estimating the object behavior without any knowledge on the environment.

3 EXTRACTION OF DYNAMICS-CORRELATED FACTORS

3.1 Outline

Outline of the proposed extraction of dynamics-correlated factors from image features is depicted in Fig.4. Image features are extracted by SIFT keypoints, as show in (1) in Fig.4. Motions of features in the image frame are approximated as a function of motor command to the robot wheels. NGnet (Normalized Gaussian networks) (Moody and Darken, 1989) is applied for the approximation so that variance of motion of features can be clustered by multiple Gaussian distributions around linear function approximators ((2) in Fig.4). NGnet is adopted because it provides not only function approximation but also estimation of variance. Gaussian process is widely used for function approximation with estimation of variance (Rasmussen and Williams, 2006), but it deals with only uniform variance in its general form. An extension of Gaussian Process to deal with input-dependent variance has been proposed (LLazaro-Gredilla and Titsias, 2011), but its calculation amount is high.

The variance of motion of features is evaluated as class probabilities to the clusters using LDA (Linear Discriminant Analysis) ((3) in Fig.4). The clusters used for LDA correspond to the Gaussian distributions composing NGnet. In comparison with PCA(Principal Component Analysis), LDA is more suitable for extracting dynamics-correlated factors since if NGnet appropriately reflects variance of dynamics through its function of clustering. Dynamics-correlated factors are extracted by analyzing correlation between the class probabilities and position of each keypoint. In this paper, we use CCA (Canonical Correlation Analysis) for calculating correlation. CCA is one of multivariate analysis method. Using CCA (Canonical Correlation Analysis), where keypoints with large correlation coefficient can be regarded to be dynamics-correlated factors ((4) in Fig.4).

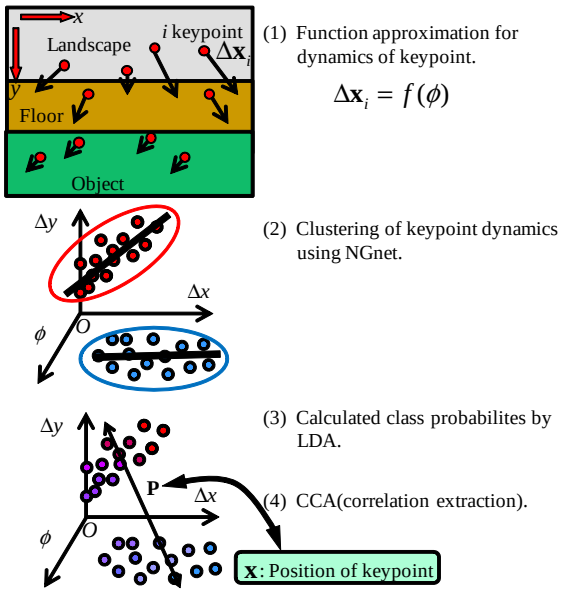


Figure 4: Outline.

3.2 Collection of Motions of Keypoints and Motor Commands

The mobile robot pushes object with various movements. Images before and after each motion of the robot are captured by its camera. SIFT keypoints are extracted in the images and matching is applied to between the two frames. Fig.5 shows an example of motions of keypoints after one cycle of robot's locomotion.

Let $m_l, m_r \in \mathbb{R}$ [step/s] denote command of rotational speed to the left and right wheels, respectively. Motor command to the robot is denoted by $\phi \in \mathbb{R}$, where ϕ specifies the rotational speeds m_r and m_l as

$$m_r = \frac{C}{2} - \phi, \quad m_l = \frac{C}{2} + \phi, \tag{1}$$

where $C \in \mathbb{R}$ is a constant. Fig.6(a) shows examples of trajectories of robot with different values of ϕ. All 128-dimensional feature vectors of SIFT keypoints over the collected images are clustered by mean shift algorithm. Matching of keypoints between two image frames is applied based on information of the obtained clusters. Let $i, i = 1, \cdots, N$ denote index of keypoint, where N denotes the total number of keypoints identified by the clustering procedure. Position of keypoint i in the image coordinate is denoted by $\boldsymbol{x}_i \in \mathbb{R}^2$ and its motion vector after the robot's locomotion is denoted by $\Delta\boldsymbol{x}_i \in \mathbb{R}^2$.

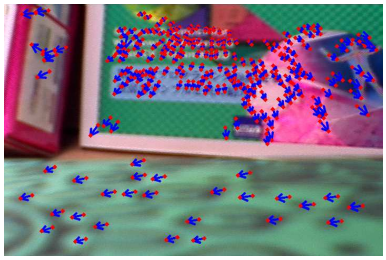
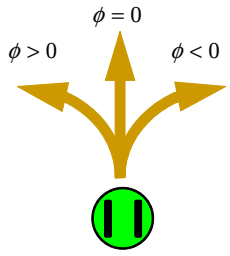
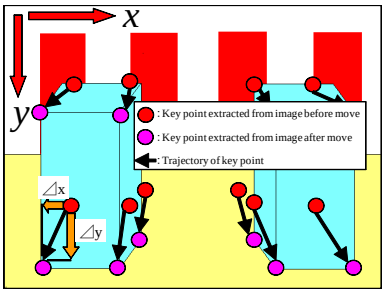


Figure 5: Example of motions of keypoints.



(a) Trajectory of robot



(b) Example of feature points data

Figure 6: Example of collecting data.

3.3 Identification of Environmental Dynamics by NGnet

Once keypoints are clustered by mean shift, motion of each keypoint is approximated by NGnet, which consists of Gaussian mixture model with linear approximators, as a function of ϕ as $\Delta\mathbf{x} = f(\phi)$. Approximation of NGnet is based on EM algorithm (McLachlan and Krishnan, 2008).

3.4 Calculation of Class Probability by LDA

LDA is applied to the multiple classes obtained by NGnet. LDA is dimensionality reduction method that maximizes the variance between classes. Average of $\Delta\mathbf{X}$ is $\Delta\bar{\mathbf{x}}$. Let $\Delta\mathbf{x}_{k,j} \in \Delta\mathbf{X}_j$ denote motion of k-th($k = 1, \cdots, n$) keypoint in class $j(j = 1, \cdots, M)$, where $\Delta\mathbf{X}_j$ denotes set of motion vectors of keypoints in class j and n_j. Within-class variance W and inter-class variance B are obtained by the following equation.

$$W = \frac{1}{n}\sum_{i=1}^{C}\sum_{\Delta\mathbf{x}\in\Delta\mathbf{X}_i}\left(\Delta\mathbf{x} - \Delta\bar{\mathbf{x}_i}\right)\left(\Delta\mathbf{x} - \Delta\bar{\mathbf{x}_i}\right)^{\mathrm{T}} \quad (2)$$

$$B = \sum_{i=1}^{C} n_i\left(\Delta\mathbf{x} - \Delta\bar{\mathbf{x}_i}\right)\left(\Delta\mathbf{x} - \Delta\bar{\mathbf{x}_i}\right)^{\mathrm{T}} \quad (3)$$

For discrimination of between two classes, it is necessary that W is as small as possible and B is as big as possible. $\mathbf{a}$ defines transformation matrix for reducing dimension of $\Delta\mathbf{X}$, and evaluation function for separation between classes $J(\mathbf{a})$ defines as following equation,

$$J(\mathbf{a}) = \frac{\mathbf{a}^{\mathrm{T}}B\mathbf{a}}{\mathbf{a}^{\mathrm{T}}W\mathbf{a}}. \quad (4)$$

Vector $\mathbf{a}$ that maximizes $J(\mathbf{a})$ is obtained as eigenvector of matrix $W^{-1}B$. Linear discriminant coefficients vector $\mathbf{d}$ is also calculated based on the obtained vector $\mathbf{a}$. Using this result, class probability of i-th keypoint P_i is estimated by $P_i = \exp(\Delta b f x_i \mathbf{d}^{\mathrm{T}})$.

3.5 Extraction of Correlation by CCA

CCA is used to extract keypoints whose positions are relevant to the change of motion dynamics. CCA is applied to class probability and position of keypoint, and correlation coefficient r is obtained. Correlation between positions of keypoints and their class probabilities are analyzed using CCA. Let P_i, $i = 1, \cdots, n$ be defined by $P_i = P(j|\Delta x_i)$, where class is specified as $j = 1$ and $M = 2$ for simplicity. Data matrices for CCA is defined as $\mathbf{P} = [P_1 \ \cdots \ P_n]$, $\mathbf{X} = [\mathbf{x}_1 \ \cdots \ \mathbf{x}_n]^{\mathrm{T}}$. Each weight coefficient of synthetic linear variable $\mathbf{U}$, $\mathbf{V}$ is $\mathbf{a} \in \mathbb{R}^{2\times 1}$, $\mathbf{b} \in \mathbb{R}^{1\times 1}$, and $\mathbf{U}$, $\mathbf{V}$ is obtained by following equation,

$$\mathbf{U} = \mathbf{a}\mathbf{X} \quad (5)$$

$$\mathbf{V} = \mathbf{b}\mathbf{P}. \quad (6)$$

r is obtained by following equation, then $\mathbf{a}$ and $\mathbf{b}$ is determined to value that r is maximum,

$$r = \frac{\mathrm{Cov}[\mathbf{U}, \mathbf{V}]}{\sqrt{\mathrm{Var}[\mathbf{U}]}\sqrt{\mathrm{Var}[\mathbf{V}]}}, \quad (7)$$

where Cov denotes covariance and Var denotes variance.

4 EXPERIMENT

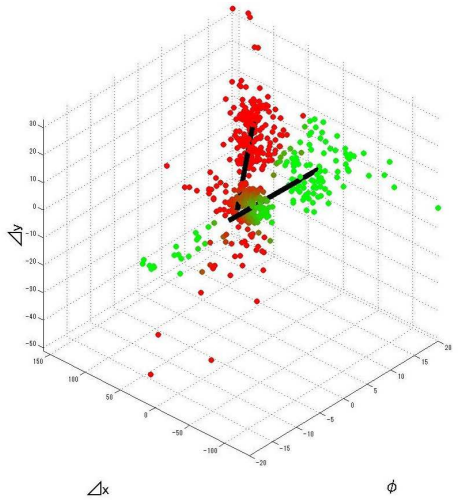
In the experiment, robot was placed in front of the object and given control input while changing ϕ in $\{-20, -15, -10, 0, 10, 15, 20\}$. The initial positions

Figure 7: Object.

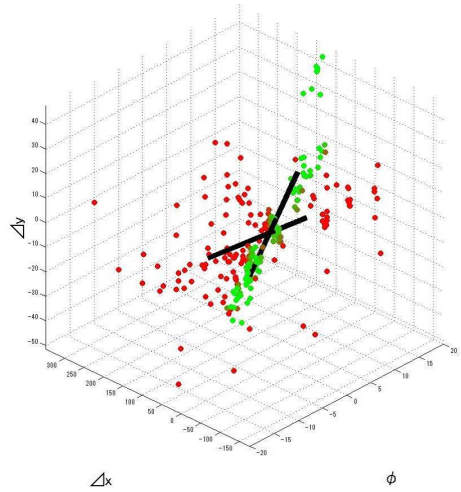
for the robot were either the center of the object (see Fig.7) or right edge of it. As a result of clustering by mean shift, totally 234 keypoints were obtained, 24 for the object and 210 for background. Pushing behavior were conducted over 100 times. Results of approximation and classification by NGnet are shown in Fig.8, with $M = 2$. Colors of points denote classes, and straight lines denote approximated linear functions, each corresponding to a class. It can be seen that in 8(a) and 8(b) of Fig.7, distribution of $\Delta \mathbf{x}_i$ could be properly estimated by two distributions. On the other hand, for some keypoints, classification into two classes was not properly done as shown in 8(c) of Fig.8, for example. This will be a cause of failure of extraction of correlation.

Distribution of correlation coefficients of keypoints for the object and background is depicted in Fig.9. As a whole, keypoints on the object showed higher correlation in comparison with those on background. It means that points on the object are more reliable to predict motions of (not necessarily, but mainly) the object. Keypoints that have high and low correlation coefficient are depicted in Fig.10. Red points denote keypoint that has high correlation, and green ones denote keypoint that has low correlation. It can be seen that keypoints with correlation are commonly extracted at the object with constantly-tractable positions in the image.

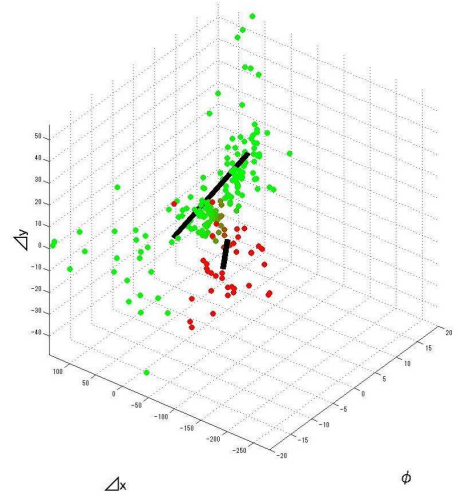
Estimated motions of keypoint of the two classes are depicted in Fig.11. Red arrow depicts motion of keypoint when robot pushed center of the object by $\phi = 0$, and blue one depicts motion of keypoint when robot pushed right edge of the object by $\phi = 0$. It can be seen that depending on the position of the keypoint, different directions of motion were predicted. It means that the robot can predict which direction the object moves depending on the position of a reliable keypoint. This prediction will help the robot to plan its action so that it can move the object to a desired location. For the purpose of prediction, errors in the process of variance approximation and correlation analysis should be further investigated.



(a) Result of NGnet 1.

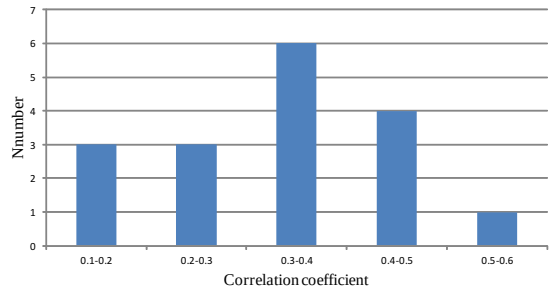


(b) Result of NGnet 2.

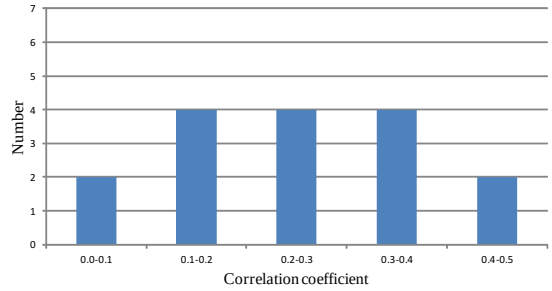


(c) Result of NGnet 3.

Figure 8: Result of NGnet.



(a) Correlation coefficients of keypoints on the object.



(b) Correlation coefficients of keypoints on background.

Figure 9: Histogram of correlation coefficient.

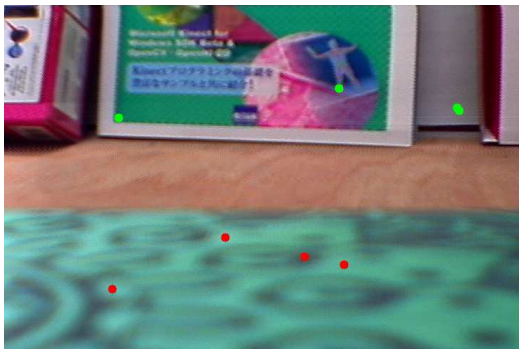


Figure 10: High and low correlation coefficient keypoint.

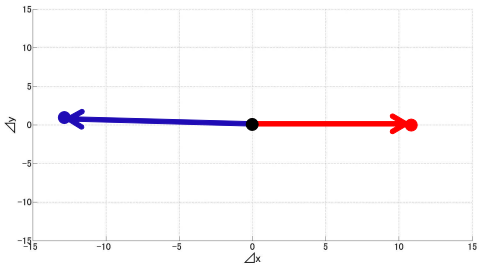


Figure 11: Estimated feature point motion.

5 CONCLUSIONS

In this paper, we proposed a method of extracting image features whose positions are influential to their dynamics. The proposed method is based on a simple motion of pushing and will be useful for higher-level motion generation. In experiment, it was verified that the proposed method showed possibility to extract useful image features for prediction of motions in the image. Distributions of motions of keypoints will be further investigated so as to realize better variance approximation.

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