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Unsupervised Body Hair Detection by Positive-Unlabeled Learning in Photoacoustic Image

Ryo Kikkawa[1], Hiroki Kajita[2], Nobuaki Imanishi[2], Sadakazu Aiso[2], and Ryoma Bise[1]

***Abstract*— Photoacoustic (PA) imaging is a new imaging technology that can non-invasively visualize blood vessels and body hair in 3D. It is useful in cosmetic surgery for detecting body hair and computing metrics such as the number and thicknesses of hairs. Previous supervised body hair detection methods often do not work if the imaging conditions change from training data. We propose an unsupervised hair detection method. Hair samples were automatically extracted from unlabeled samples using prior knowledge about spatial structure. If hair (positive) samples and unlabeled samples are obtained, Positive Unlabeled (PU) learning becomes possible. PU methods can learn a binary classifier from positive samples and unlabeled samples. The advantage of the proposed method is that it can estimate an appropriate decision boundary in accordance with the distribution of the test data. Experimental results using real PA data demonstrate that the proposed approach effectively detects body hairs.**

I. INTRODUCTION

Photoacoustic (PA) imaging is a non-invasive visualizing method that can visualize the 3D structure of blood vessels and body hair. In the PA imaging process, tissue is irradiated by a laser and emits the absorbed laser energy as ultrasonic waves. The 3D structure of the tissue can be visualized by sensing the ultrasonic waves [1]. In addition to blood vessels, body hair has the PA characteristics (Fig. 1). Metrics of body hair, such as the number and thickness of hairs, are useful in research on alopecia and cosmetic surgery. Since it is time-consuming to detect many hairs in clinical practice, a method to automatically detect body-hair is desired.

Traditional image-processing approaches have limitations, since body hairs and blood vessels often touch each other along with PA artifacts. On the other hand, supervised learning, such as convolutional neural network (CNN)-based segmentation [2], works if the imaging condition between training and test data is the same. However, the setup of the imaging device and the patient often differ in practice. Kikkawa *et al.* [3] proposed semi-supervised learning, which is widely used in computer vision [4], [5], for body hair detection. However, it also has the same drawback. Many labeled samples are required to learn a body hair classifier that works robustly for various setup. However, it is expensive to make such annotated data from 3D volume images, and the available data are limited because PA imaging is a new technology.

The aim of this study is to learn discriminative features of body hairs for an input image without any manual annotations. Fig. 2 shows our framework. The key idea of

[1] with Kyushu University, bise@ait.kyushu-u.ac.jp
[2] with Keio University Hospital

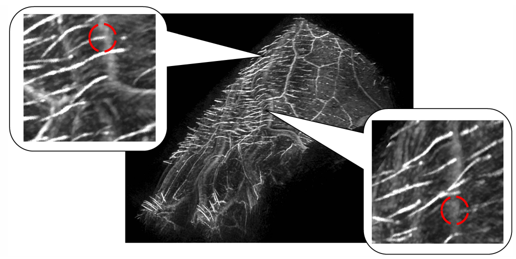

Fig. 1. Example of 3D volume captured by PA imaging. Body hair often touch blood vessel as shown in the red circle and body hairs have various intensities.

this study is that the unlabeled candidate's regions, which may belong to a body hair or other regions, can be detected using image processing and a subset of positive samples can be automatically extracted from unlabeled samples on the basis of prior knowledge of spatial structure, in which body hairs usually appear on the surfaces of the body.

As a result, we can obtain positive labeled samples and unlabeled samples, and this enables positive-and-unlabeled (PU) learning [6], [7], which learns a binary classifier only from positive samples and unlabeled samples, to be applied to this task. One important idea is to extract positive samples by using features different from those in the feature space used during PU learning. Not only PU learning but also general machine learning methods need to use sample data sampled at random from the population. Therefore, it is important to design the features used during PU learning so that they do not correlate with the features used during positive example extraction. Experiments demonstrate that our method can detect body hairs without any human annotation. The advantage of our approach is that it can estimate appropriate decision boundaries according to the distribution of the test data. Accordingly, complicated annotations can be omitted and applications to various fields can be expected.

Related work: Positive-and-unlabeled (PU) learning [6] is a promising novel machine learning problem that performs binary classification from positive labels and unlabeled samples. Many methods have been proposed for ensemble learning [8], Bayes classifier [9], and time series classification [10], and PU learning has been applied to several applications, particularly text analysis: opinion analysis [11], spam detection [12], and gene expression analysis [13]. These methods assume that positive samples are given with supervised labels, which is the original problem setup. In contrast to the current methods, we use PU-learning for the unsupervised problem by automatically detecting a subset of positive samples using prior knowledge of spatial structures.

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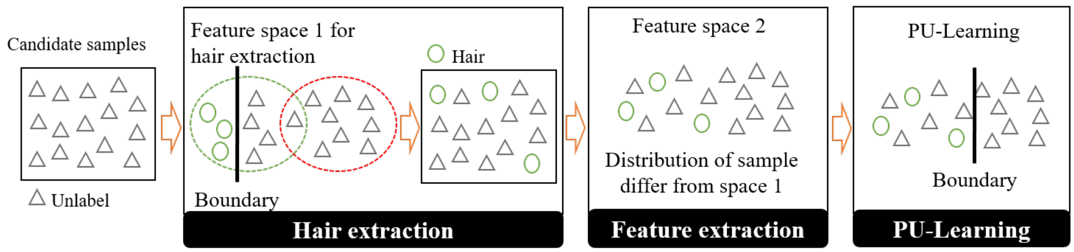

Fig. 2. Overview of proposed framework

II. Unsupervised body hair detection by PU learning

In this section, we explain the proposed method for detecting hair in a PA image that can reformulate the original detection problem as the PU learning problem. First, the method detects hair candidate regions redundantly from a 3D volume PA image. PU learning is possible because a subset of hair samples is automatically extracted from unlabeled samples by using prior knowledge of spatial structures in the image. If a low recall score is allowed, it is easy to extract some positive hair regions. Then, given positive labeled samples and unlabeled samples, we use PU learning to classify unlabeled candidate regions into hairs and other regions, in which we use different features for classification from those used for positive sample extraction in order to maintain the randomness of the extracted positive sample distribution in the feature space. One key point is that this process is performed on each test data. The proposed method learns a discriminative feature distribution for each test data; thus, it is not restricted by the imaging setup or the condition of the patient.

A. Hair candidate region detection

It is difficult to recognize hair regions at the voxel level because regions of hairs and blood vessels have locally similar features, in which the intensity distribution is similar, and voxels with high intensity form cylindrical shapes. On the other hand, each object in an image has features useful for identifying differences in the intensity distribution. In this research, we aim to recognize body hairs at the object level.

The goal of this step is to make candidate regions redundantly so that most true positives are included in the candidate set. As we discussed in the introduction, there are many body hairs near blood vessels. Since radial artifacts often appear around an object, the intensities of the regions between the body hair and the blood vessels are higher than the background level, and the brightness may take on various values. Thus, it is difficult to separate the regions by using a single threshold. To address this, we follow the detection method proposed by Kikkawa et al.[3]. Because the intensity of the artifact is usually slightly less than the sound source (i.e., vessels and hairs), candidate regions are extracted by using multiple-level thresholds to separate all the regions. We set K thresholds and used each threshold to segment images into candidate regions and background.

These candidates can be considered as unlabeled data since these may contain both of body hairs and other noise regions.

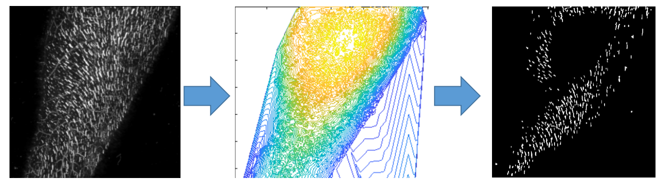

Fig. 3. Overview of automatic extraction of body hair; Left: original image, Middle: results of surface fitting, Right: extracted positive samples.

B. Automatic extraction of body hair using prior knowledge of spatial structures in photoacoustic volume

In this step, we automatically identify the subset of positive samples from these candidates. We use prior knowledge of the structure of the photoacoustic image space: many body hairs appear along the body surface, and some of them are above the blood vessels (although not always). The body surface can be roughly estimated by fitting the 3D points of the object in the photoacoustic volume by using robust regression [14]. Using this body surface as a threshold in the height direction in the volume, a candidate region located above it is determined to be body hair, and is regarded as a positive sample in the training data. Fig. 3 shows the example results by this step. The precision of the extracted body hair regions is high, although the method cannot extract all body hairs, in which the other body hairs remain in the other candidate regions. This indicates that the extracted regions can be considered as the subset of positive samples, and the other candidate regions extracted in the previous step can be considered as unlabeled samples (positive or negative).

C. Feature extraction for PU learning

PU learning assumes that the extracted positive samples must be randomly distributed in all the positive samples in the feature space used for PU learning. Because we used the position of body hairs in a body, we cannot use this feature for PU learning in order to avoid the lack of the randomness. In our observation, the position of hairs in the body is not correlated with the intensity feature of hairs; the regions of hairs placed near the surface have various intensity values, and the deeper area contains both low-and-high-intensity hairs. We simply use the intensity-based features proposed in [3]. We expect that the positive samples extracted in the previous step tend to be randomly distributed in this intensity-based feature.

D. PU learning

Given positive samples identified as body hairs and other unlabeled samples, we use PU learning to classify whether a sample is a body hair or not. To make the paper self-contained, we explain two methods of PU learning below; error minimization [6] and area under the curve (AUC) maximization [7].

1) PU learning based on error minimization: We first explain the general binary classification problems. An appropriate classifier can be learned by minimizing a risk function as follows:

$$R_{PN}(g) = \pi E_P[l(g(X_P))] + (1-\pi)E_N[l(-g(X_N))], \quad (1)$$

where π is the prior probability of the positive samples, l is the loss function, g is the classifier, and positive samples X_P (class label $y = 1$) and negative samples X_N (class label $y = -1$) occur according to the distribution of $p(x|y)$. The first term on the right side represents the loss when a positive sample is mistaken as a negative sample, and the second term represents the loss when a negative sample is mistaken as a positive sample.

PU learning needs to learn the classifier from only a subset of positive examples and unlabeled samples, which include positive and negative examples; thus, it cannot directly calculate the second term in the function (Eq. 1). If an unlabeled sample is used as a negative sample, excessive loss may occur. An objective function that can be optimized using cost-sensitive learning is

$$R_{PU}(g) = \pi E_P[l(g(X_P)) - l(-g(X_P))] + E_U[l(-g(X_U))], \quad (2)$$

where X_U is unlabeled samples. In the first term, when a positive sample can be classified as such, the excess loss in the second term is offset by outputting a negative value. To find a globally optimal solution in practice, a surrogate loss composed of a convex function, such as the logistic loss, is selected. According to research by Plessis et al.[6], learning to minimize this function (Eq. 2) is equivalent to minimizing the function (Eq. 1). The positive prior probability π in the training data needs to be estimated for optimizing the objective function, and the distribution must be estimated from unlabeled data. However, in our data, we do not always know the ratio of the positive samples.

2) PU learning based on AUC maximization: We introduce the blind AUC (BAUC) maximization method that applies the existing AUC maximization to the PU problem by considering unlabeled samples as negative samples.

In general PU classification tasks, the number of training samples is often biased to one class, and negative samples are dominant in most cases. At this time, it is difficult to minimize the expected loss, and hence, the decision boundary would be wrong. On the other hand, AUC is suitable for evaluating the classifier in the PU classification task, AUC is invariant to the ratio of positive samples in the training data. In addition, there is an advantage that it is not necessary to estimate the prior probability of positive samples when learning.

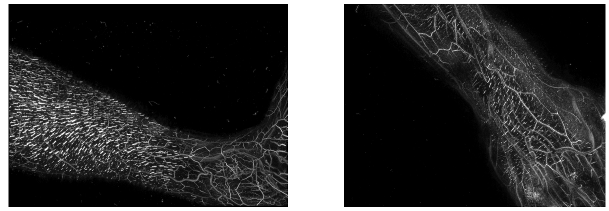

Fig. 4. Maximum intensity projection images of 3D volumes used for experiments for data 1 (Left) and data 2 (Right), in which the image contrast manually was adjusted for visualization purpose. The number and the intensity of body hairs are significantly different between the data.

TABLE I

THE SAMPLE NUMBER ASSIGNMENTS

	Body hair	Other	Extracted body hair
Data 1	2120	4612	476
Data 2	978	6466	184

The goal is to update the learning parameters to maximize AUC, but in the PU classification task, negative samples are not available, so the value of the AUC cannot be obtained directly. Therefore, in the proposed method, the unlabeled samples are blindly considered to be negative samples. The function $\mathrm{B\widehat{AUC}}$ for this pseudo AUC is shown below.

$$\mathrm{B\widehat{AUC}}(f) := \frac{1}{n_U n_P} \sum_{\substack{x_U \in X_U, \\ x_P \in X_P}} \mathbf{1}(f(x_P) > f(x_U)), \quad (3)$$

where the ranking function f is a linear sum of the input and weight, and n_U and n_P are the number of unlabeled samples X_U and positive samples X_P. According to research by Ren et al.[7], maximizing this function (3) is theoretically equivalent to maximizing the standard AUC.

Maximizing $\mathrm{B\widehat{AUC}}$ is equivalent to minimizing $1-\mathrm{B\widehat{AUC}}$ as follows

$$\min_f 1 - \mathrm{B\widehat{AUC}}(f) = \frac{1}{n_U n_P} \sum_{\substack{x_U \in X_U, \\ x_P \in X_P}} \mathbf{1}(f(x_P) \leq f(x_U)). \quad (4)$$

This function penalizes when ranking function scores of positive samples is larger than that of unlabeled samples. In other words, when all samples are arranged in ascending order of the ranking function score, this function is optimized such that the scores of the positive samples are higher than those of most unlabeled samples.

III. EXPERIMENT

A. Dataset

We evaluated our method on two real 3D PA volume datasets captured from patients, in which the total number of hairs is 3098. For simplicity, IDs 1 and 2 were assigned to each volume (Fig. 4). In these two images, the numbers and the intensities of the body hairs are significantly different. To generate the ground truth for evaluating performance, we annotated the endpoints of body hairs for two real 3D PA volumes. In the experiment, positive samples were automatically extracted, and other candidate regions were trained as unlabeled samples. Table I shows the sample number assignments for the hair class, other class, and the automatically extracted hair class in each volume.

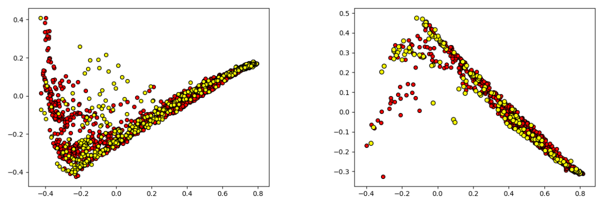

Fig. 5. Visualization of feature distribution using by PCA for Data1 (Left) and Data2 (Right). Red and yellow circles indicate true and pre-extracted hair samples, respectively.

TABLE II

RESULTS OF AUC EVALUATION EXPERIMENT

Method	Data1	Data2
Surf. Fit.	0.651	0.727
ERR(10%)	0.337	0.809
ERR(20%)	0.747	0.894
ERR(30%)	0.870	0.913
ERR(40%)	0.897	0.916
ERR(50%)	0.910	0.916
BAUC	0.910	0.916

B. AUC evaluation on two PU learning methods

We tested a image processing-based method and two PU learning methods using automatically extracted body hair samples and unlabeled samples: 1) the body hair regions were extracted by multi-thresholding and surface fitting (Surf. Fit.), in which the AUC was computed by moving the surface curves, 2) error minimization (ERR), 3) BAUC maximization (BAUC), and quantitative evaluation using AUC values for comparison[1]. The learning and evaluation were performed independently for each volume. The loss function of each method was the logistic loss, $\log(1+\exp(-z))$. In addition, since in practice, the prior probability of positive samples π cannot be given in the error minimization method, we evaluated the method using five π values (10 to 50 %).

Table II summarizes the AUC values obtained by each method. The image processing-based method (Surf. Fit.) could not work well since the parts of vessel regions have similar appearances to body hairs. For ERR, the AUC values fluctuated sensitively to changes in the given prior probability of the positive samples. The tendency was prominent in data 1, and the AUC values tended to deteriorate as the value of the small prior probability was decreased. This is because the number of hair class samples in the training data was extremely small and the loss when mistaking a positive sample as an unlabeled sample is negligible. On the other hand, for BAUC, AUC values were stable for all images.

C. Visualization of feature distribution

To analyze if the assumption of PU learning, in which positive samples are randomly sampled in the feature space, is true in the experiments, we qualitatively evaluated the feature distribution of the true hair class and the automatically extracted body class. For visualization, the 33 dimensions of feature vectors were reduced to 2 dimensions by using principal component analysis (PCA); these are plotted in Fig. 5. The extracted body hairs are distributed similarly to that of the population. Therefore, to some extent, this validates the assumption by extracting positive samples from features other than the feature space used for PU learning.

[1]No existing method can detect body hairs in un unsupervised problem setup.

IV. CONCLUSION

We proposed an unsupervised body hair detection method in photoacoustic 3D images. Our main contribution is that we reformulate the detection problem as a Positive-Unlabeled (PU) learning problem setup and the subset of positive samples is automatically extracted by using prior knowledge on spatial structures in the photoacoustic volume. Experimental results revealed that our method can detect body hairs with an unsupervised setup. The advantage of our approach is that it can estimate appropriate decision boundaries according to the distribution of the test data. Accordingly, complicated annotations can be omitted and applications to various fields can be expected.

Compliance with ethical standards: This work was performed with the approval granted by the Ethics Committee of Keio University School of Medicine (Date Mar. 30/2018 /No. 20170158). There is no conflict of interest for authors.
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