8th IEEE International Conference on Advanced Video and Signal-Based Surveillance, AVSS 2011, IEEE 2011. 101-106

DOI: http://dx.doi.org/10.1109/AVSS.2011.6027302

Discrimination of abandoned and stolen object based on active contours

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Abstract

In this paper we propose an approach based on active contours to discriminate previously detected static foreground regions between abandoned and stolen. Firstly, the static foreground object contour is extracted. Then, an active contour adjustment is performed on the current and the background frames. Finally, similarities between the initial contour and the two adjustments are studied to decide whether the object is abandoned or stolen. Three different methods have been tested for this adjustment. Experimental results over a heterogeneous dataset show that the proposed method outperforms state-of-art approaches and provides a robust solution against non-accurate data (i.e., foreground static objects wrongly segmented) that is common in complex scenarios.

1. Introduction

Nowadays, there is a growing video surveillance demand as a consequence of the increasing global security concern which turned into a massive system deployment [1]. Traditionally, the monitoring task is performed by a human operator who has to simultaneously process a huge amount of visual data. Therefore, a significant efficiency reduction is expected. Automatic video interpretation was proposed as a solution to overcome this limitation.

In this situation, the detection of abandoned and stolen objects has become one of the most promising research topics especially in crowded environments such as train stations and shopping malls. It presents several challenges related to lighting conditions, object occlusions and object classification. Moreover, since these potential abandoned or stolen objects may have arbitrary shape and color, specific object recognition methods can not be applied.

Many methods have been proposed for abandoned and stolen object detection focusing on the stabilization of the image sequence from a moving camera [2], based on the static foreground region detection [3], based on blob classification (e.g., between people and object) [4] or dealing with the discrimination of the static regions between abandoned or stolen [5]. They yield acceptable results in simple scenarios where high analysis accuracy is expected. However, this is not always valid for complex situations where a performance decrease may occur.

In this paper, we propose an approach based on active contours for the discrimination of static foreground objects between abandoned and stolen. It provides a robust solution against non-accurate segmentations of stationary objects in the analyzed video sequence. Starting from an initially extracted contour, active contour technique is applied to check whether the object contour is present in the current or in the background image and thus, decide if the object has been abandoned or stolen. Three different active contour methods have been tested based on edge and region information. Finally, this proposal is evaluated over a heterogeneous dataset with sequences with varying complexity and compared against state-of-art approaches.

This paper is structured as follows: section 2 discusses the related work; in sections 3 and 4 we overview the proposed discriminator and the selected active contours methods, experimental results are given in section 5, whilst section 6 ends the paper with the conclusions.

2. Related work

Abandoned and stolen object detection comprehends several tasks such as foreground extraction [2], static region analysis [3], blob tracking [6], blob classification (such as people [7] or baggage [8] recognition) and discrimination between abandoned or stolen objects.

Focusing on the discrimination of static foreground regions between abandoned and stolen, some of the existing approaches simplify this problem by assuming that only object insertions are allowed (i.e., detection of stolen objects is forbidden) and, therefore, all static objects are abandoned objects [2][6][8]. However, this assumption does not provide solutions for common artifacts generated by the background subtraction technique (e.g., ghosts) limiting the potential application of these proposals. On the other hand, few approaches have been proposed for this discrimination. Among existing literature, we can classify them according to the nature of the employed features into *edge-based*, *color-based* and *hybrid*.

Edge-based methods rely on inspecting the energy of the static region boundaries. It assumes that this energy is high in the current frame for abandoned objects and low for stolen objects. For example, [9] proposed a system that analyzes the change in edge energy, and determines that an object has been added to the scene if the energy in the current frame is significantly higher or lower. Similarly, [10][11] proposed to use a Canny edge detector inside the bounding box of the static region in both the background and the current frame, and then they are compared to determine whether the object has been removed from or added to the scene. Moreover, [12] described a matching method to compare the results of the SUSAN edge detection in the current frame and foreground mask.

Color-based methods use the color information extracted from the internal and external regions delimited by the bounding box and the contour of the static region. In [7], two Bhattacharya distances are computed between the color histograms of the internal (in the current and background frames) and the external (in the background frame) regions. Discrimination is determined as the lowest distance. Similarly, a color-richness measure is proposed in [13] to count the number of colors (i.e., histogram bins above a threshold) and perform the same comparison as [7]. Moreover, [14] proposed to use image inpainting to reconstruct the hidden background and compare it against the external region using color histograms. Additionally, [15] compares color information within and outside the candidate static region by using segmentation techniques.

Hybrid discriminative methods combine the previous approaches. For example, [5] fused two algorithms based on edge and color by building probabilistic models for each algorithm in both cases (abandoned or stolen). Then, the decision is given by the maximum average probability of each case. Furthermore, [16] combined several features related with the edge energy, color contrast and shape into a classifier by using generative models for them.

In conclusion, the different techniques found in the recent literature use either edge or color information to perform the abandoned/stolen discrimination. Although these methods work well for simple scenarios, they have difficulties in complex scenarios as they do not consider the possibility of occlusions or complex backgrounds (e.g., high textured backgrounds). In addition, these methods rely on the precision of foreground object detection, and they may perform poorly in complex scenarios.

3. Discrimination based on active contours

A new approach based on active contours is proposed for discriminating static objects between abandoned and stolen. Let the initial contour of the static object, at time *t*, be defined as $C_t^I = \{p_1 \ldots p_i . . p_N\}$ and obtained as follows:

$$C_t^I = h(F_t, M_t), \tag{1}$$

where $h(.)$ represents the contour extraction algorithm; F_t and M_t the current frame and foreground mask of the static object; p_i is the *x,y* coordinates of the *ith* contour point and N is the number of contour points. In our approach, $h(.)$ is a simple point-scanning of the result after applying the Canny edge detector to the M_t mask. This contour indicates the boundaries of the inserted (i.e., abandoned) or removed (i.e., stolen) of the scene object.

Then, a fitting process of the contour C_t^I is performed on the current and the background frame by using active contours. Thus, two adjusted contours are obtained.

$$C_t^{\mathrm{EF}} = f(F_t, C_t^I), \tag{2}$$

$$C_t^{\mathrm{EB}} = f(B_t, C_t^I), \tag{3}$$

where $f(.)$ represents the contour adjustment method; F_t and B_t are the current and background frames; C_t^I is the initial contour; C_t^{EF} and C_t^{EB} are the adjusted contours in the current and background frames. For abandoned objects, the adjusted contour will be attracted to object boundaries in the current frame, and thus it will be similar to the initial contour. Conversely, the contour is expected to be deformed in the adjustment using the background frame as there are no object boundaries. In most cases, this uncovered area does not have strong edges and the contour may shrink or disappear. For stolen objects, the adjustment result will be the opposite; it will be attracted in the background frame and deformed in the current frame.

After that, a similarity measure is defined to quantify the deformation of the initial contour. We have decided to use the Dice coefficient [17], which is defined as follows:

$$\mathrm{d}(\mathrm{C}_1, \mathrm{C}_2) = \frac{2|\mathrm{A}_1 \cap \mathrm{A}_2|}{|\mathrm{A}_1| + |\mathrm{A}_2|} \tag{4}$$

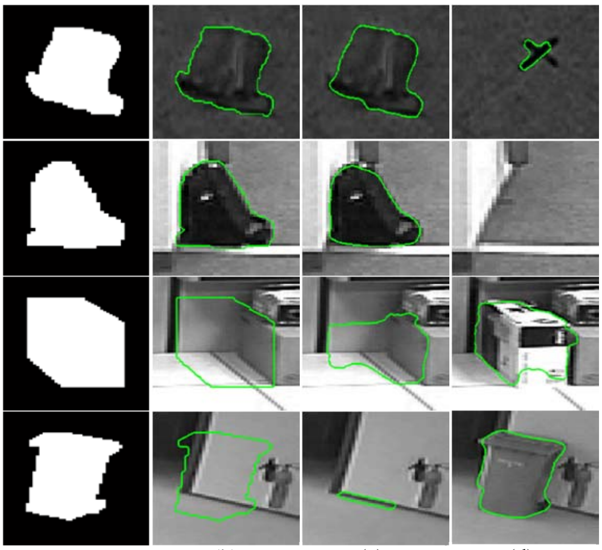
where $\mathrm{C}_{1,2}$ represent two contours, $|\mathrm{A}_1 \cap \mathrm{A}_2|$ is their spatial overlap (in pixels); $|\mathrm{A}_1|$ and $|\mathrm{A}_2|$ represent the area (in pixels) of each contour. Thus, we obtain two distances (d_t^F and d_t^B) from the comparison of the initial contour C_t^I with the adjusted contours C_t^{EF} and C_t^{EB}. The values of d_t^B will be close to 0.0 and 1.0 in case of, respectively, abandoned and stolen objects. Distance d_t^F will get opposite values. Afterwards, a score is obtained by combining both distances as follows:

$$s_t = d_t^F - d_t^B \tag{5}$$

Finally, the discrimination is performed by thresholding the final score s_t as follows:

$$D = \begin{cases} abandoned & if \quad s_t > th \\ stolen & if \quad s_t \leq th \end{cases} \tag{6}$$

where *th* is the threshold applied for taking the abandoned or stolen decision, and is obtained from a training sequence. Figure 1 shows examples of the contour adjustments for abandoned and stolen cases.



(a) (b) (c) (d)

Figure 1: Examples of the proposed discrimination approach for abandoned (rows 1&2) and stolen (rows 3&4) objects. (a) Foreground mask, (b) initial contour and contour adjustment for the (c) current and (d) background frames.

4. Selected active contour algorithms

Up to this point, an approach for discriminating static foreground objects has been defined depending on a contour adjustment function $f(.)$. According to [18], active contours methods can be either parametric or geometric considering whether their contour representation is explicit [19] or implicit (using level sets [18][20]). Moreover, we can further differentiate between methods based on boundaries or regions. We have tested the most representative methods in our approach.

4.1. Parametric active contours

We first consider the classic active contour model [19]. Starting from an initial contour $C = \{p_1 \dots p_N\}$, it iteratively minimizes a global energy function defined as:

$$E = \sum_{i=1}^{N} \alpha_i E_{cont} + \beta_i E_{curv} + \lambda_i E_{imag} \qquad (7)$$

where N is the number of contour points, E_{cont} is the continuity energy, E_{curv} is the curvature (i.e., smoothness) energy, E_{imag} is the external energy (e.g., image edges) and $\alpha_i, \beta_i, \lambda_i \geq 0$ are the weights of each energy. These energies are defined as:

$$\begin{aligned} E_{cont} &= \|p_i - p_{i-1}\|^2 \\ E_{curv} &= \|p_{i-1} - 2p_i + 2p_{i+1}\|^2 \\ E_{imag} &= gradient(I_t) \end{aligned} \qquad (8)$$

In our approach, we remove redundant edge data to compute the E_{imag} energy (i.e., edges that are present in current and background images). First, we have applied the *Canny* edge operator to each RGB channel of the current and the background frame. Then, the channel edge maps are combined using the logical operation OR. Finally, edges that appear in the background and current frame are removed to obtain the relevant edge data.

To achieve best results, parametric active contours algorithms such as this one require the initial contour to be initialized close to the true boundary. This holds true for abandoned objects, since the final contour is expected to be close to the initial contour. However, this limitation may be problematic when there are stolen objects. Although very simple to develop, traditional active contour models depend on the correct initialization.

4.2. Geometric active contours

Geometric active contour methods are proposed to solve the limitations of the parametric approaches by assuming an energy formulation invariant with respect to the curve parameterization. The contour is represented as the zero level set $\phi^{-1}(0) = \{(x,y)|\phi(x,y) = 0\}$ of a scalar function $\phi(x,y)$ usually referred as the level set function. The evolution of this function is guided by an energy minimizing process.

4.2.1 Geometric region-based active contours

A natural extension to overcome limitations of boundary analysis is the processing of regions. Among existing region-based approaches, we have selected the widely referenced work described in [20]. Derived from the Mumford-Shah energy functional for segmentation [20], piecewise constant functions are defined considering the intensity means of the different regions delimited by the contour. These cost functions are defined as follows:

$$E = \lambda_1 \int_{in(C)} |I(x,y) - m_{in}(C)|^2 dxdy \qquad (9)$$

$$+\lambda_2 \int_{in(C)} |I(x,y) - m_{out}(C)|^2 dxdy + \mu L(C) + \alpha A(C)$$

where $m_{in}(C)$ and $m_{out}(C)$ are the mean intensity value of the internal and external regions delimited by the contour; *L(C)* is the length of the contour*; A(C)* is the area of the contour; λ_1, λ_2, α and μ are fixed positive parameters. Then, a minimization problem is considered:

$$\min_{m_{in}, m_{out}, C} E\,(m_{in}, m_{out}, C) \qquad (10)$$

To compute this optimization, level set optimization is jointly performed with the estimation of mean intensity values attempting to recover two regions such that

$|m_{in}(C) - m_{out}(C)|$ is maximum whilst assuring regularity properties for these regions. This model overcomes certain limitations of traditional parametric methods. It can detect objects with smooth boundaries (weak gradient) and it is more robust to noise. Moreover, contour initialization can be done at a higher distance from the real contour than the parametric approaches.

4.2.2 *Geometric edge-based active contours*

Extending the geometric methods based on level sets, [18] proposed an edge-based method to eliminate the re-initialization of the level set method that moves the zero level set from its original location extracting wrong contours. A new energy term is included to force the level set function to be close to a signed distance function. Thus, the proposed cost function to be minimized is:

$$\mathcal{E}(\phi) = \mathcal{E}_m(\phi) + \mu\mathcal{P}(\phi) \quad (11)$$

where $\mathcal{E}_m(\phi)$ is the external energy that adjusts the zero level set (i.e. contour) to the image boundaries; $\mathcal{P}(\phi)$ is the internal energy that penalizes the deviation of the level set function from a signed distance function; ϕ is the level set function and μ is a fixed positive parameter to control the influence of the internal energy. The external energy, $\mathcal{E}_m(\phi)$, is composed of two terms:

$$\mathcal{E}_m(\phi) = \lambda\mathcal{L}_g(\phi) + \nu\mathcal{F}_g(\phi) \quad (12)$$

where $\mathcal{L}_g(\phi)$ is the length of the zero level curve of ϕ; $\mathcal{F}_g(\phi)$ is the speed of the curve evolution; g is a weight indicator function based on edges; $\lambda > 0$ and ν are the parameters to weight the energy contributions. Particularly, the parameter ν can be used to expand ($\nu > 0$) or shrink ($\nu < 0$) the evolution of the contour depending on whether the initial contour is placed outside or inside the object. We can take advantage of this behavior in the case of stolen objects, driving the motion of the curve and causing it to shrink. Abandoned objects will not be affected since the initial contour is already close to the object boundaries.

5. Experimental validation

5.1. Setup

We have carried out experiments using annotated and real data. The proposal has been implemented in C++ using the OpenCV image processing library[1]. Tests were executed on a P-IV (3.0GHz) with 2GB RAM. Moreover, we compare the versions of our proposal (PE[19], GR[20] and GE[18],) against the most popular methods based on edge energy (ED[12]) and color-histogram (CH[7]).

[1]http://sourceforge.net/projects/opencvlibrary/

Table 1: *Test sequences categorization.*

Category	Number of annotations		Background complexity
	Abandoned	**Stolen**	
C1	841	252	Low
C2	520	200	Medium
C3	671	480	High
Total	2032	932	-

For the experiments with annotated data, we have selected several sequences from the PETS2006[2], PETS2007[3], AVSS2007[4], CVSG[5], VISOR[6], CANDELA[7] and WCAM[8] public datasets. The annotations[9] consist of the foreground binary masks of the abandoned or stolen objects. For performance evaluation, we have divided all the annotations into three categories according to the background complexity in terms of the presence of edges, multiple textures and objects belonging to the background. Table 1 summarizes the annotated content of the dataset. Finally, ROC curves are employed for the evaluation.

To find the optimum parameters of the active contour algorithms, we have proceeded as follows. For the PE algorithm, different combinations for parameters α, β and λ were considered ranging from 0.0 to 3.0 (with a step size of 0.01). Optimal achieved configuration was $\alpha = 0.97, \beta = 1.30, \lambda = 0.52$. In addition, the optimal size of the search window was determined to be 5. For the GR algorithm, we have used the proposed default values for the following variables: $\lambda_1 = 1$, $\lambda_2 = 1, \nu = 0, h = 1$, and $\Delta t = 0.1$. The α and μ were empirically defined ($\alpha = 1.0$ and $\mu = 0.05 \cdot 255^2$). For the GE algorithm, we have used a slightly higher time step to reduce the iterations needed ($\Delta t = 15$). For parameters λ, μ and ν; best results were obtained with $\lambda = 5, \mu = 0.0133, \nu = 1.8$.

5.2. Evaluation with annotated data

A summary of the experiments is shown in Figure 2 and Table 2. As it can be observed, the proposed approach outperforms the state-of-art methods having higher AUC (Area under curve) values. The existence of complex backgrounds reduces the accuracy of the state-of-art methods as they assume low-textured background with little edge information. Our proposal is robust against this kind of complexity. Among the selected active contour methods, GE obtained the best results. For all methods, the contour is accurately adjusted when the object boundaries are present (i.e., current and background frames for, respectively, the abandoned and stolen cases). However,

[2]http://www.cvg.rdg.ac.uk/PETS2006/
[3]http://www.cvg.rdg.ac.uk/PETS2007/
[4]http://www.avss2007.org/
[5]http://www-vpu.eps.uam.es/CVSG/
[6]http://www.openvisor.org/
[7]http://www.multitel.be/~va/candela/
[8]http://wcam.epfl.ch/
[9]Available at http://www-vpu.eps.uam.es/ASODds

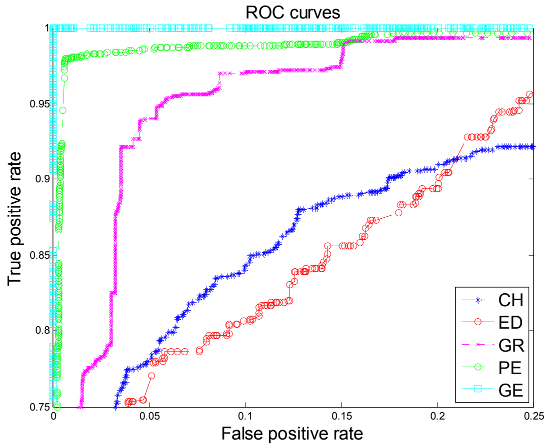


Figure 2: ROC curves for the discrimination of static objects between abandoned and stolen using the evaluation dataset.

their results differ for the adjustment without boundaries (i.e., background and current frames for, respectively, the abandoned and stolen cases). For PE, the deformations are not substantial, unless the initial mask belongs to a small object. For GR, sometimes the adjustment turns into a contour expansion limited by its bounding box size. Thus, the similarity measure (Eq. 4) exhibits a lower bound for expansion cases that depends on the contour area and its bounding box. To decrease this bound, the bounding box size can be extended. However, the computational cost of the adjustment is increased. In our experiments, the bounding box was increased by a factor of 1.5 as a trade-off between accuracy and time. GE overcomes this problem by allowing us to control the contour adjustment (expansion or shrinkage) with the selected value for parameter ν. Thus, GE showed better results, as the contours shrink considerably or completely disappear.

Table 3 describes the computational cost results. Maximum and minimum values correspond to, respectively, large and small objects. As it is shown, state-of-art approaches have lower cost (as they perform simple operations) than the active contour ones. Among them, edge-based methods are faster than region-based methods as they consider local data (e.g., edges in a neighborhood) instead of global data (e.g., region statistics). Despite the higher cost of our approach, it should be noted that this analysis is not typically performed on a frame-by-frame basis and a slightly higher cost can be affordable.

5.3. Evaluation with real data

For the experiments with real data, we have selected some sequences of the above-mentioned datasets. A state-of-art abandoned/stolen object detection system has been implemented to get real data (i.e., masks of static foreground objects) [5]. Figure 3 shows the obtained contour adjustments using real data and Table 4 their corresponding scores (incorrect scores are marked using

Table 2: *Comparative results for the ROC analysis*

Category	Area Under Curve				
	PE	GR	GE	CH	ED
C1	1.0	0.99714	1.0	0.99754	0.97721
C2	0.99539	0.97788	1.0	0.95049	0.89105
C3	0.99240	0.97029	1.0	0.88167	0.94099
Total	**0.99617**	**0.98475**	**1.0**	**0.94396**	**0.94**

Table 3: *Comparative computational cost (ms)*

Computational Cost	Time (ms)				
	PE	GR	GE	CH	ED
Minimum	2.30	69.21	20.78	5.67	0.14
Maximum	1401.80	865.70	1187.10	44.57	130.87
Average	234.47	273.01	246.39	23.23	28.36

bold font). While PE and GR are able to perform correct detection in most cases, GE still produces more accurate adjustments, leading to higher class separability (i.e., difference between the scores of the abandoned and stolen cases). In addition, it can be seen that the Dice coefficient distance comparison between shapes produces satisfactory results even when the contour is attracted to nearby objects instead of shrinking or disappearing in those frames in which the object is not present (background frame for the abandoned case, and current frame for the stolen one), thus allowing the detectors to perform better in more complex scenes.

6. Conclusions

We have proposed a new approach for discriminating abandoned and stolen objects in video surveillance. It is based on adjusting the contour of candidate static foreground region to the current image and the reference background. Three different active contour strategies have been tested. Experiments on annotated and real data show that the proposed approach is significantly better than the state-of-art approaches. Geometric active contours based on edge information obtained the best results due to the more accurate adjustments obtained on images where the object is not present, making the contour disappear in many cases and adding robustness to the detector.

7. Acknowledgments

This work has been partially supported by the Consejería de Educación of the Comunidad de Madrid and by The European Social Fund.

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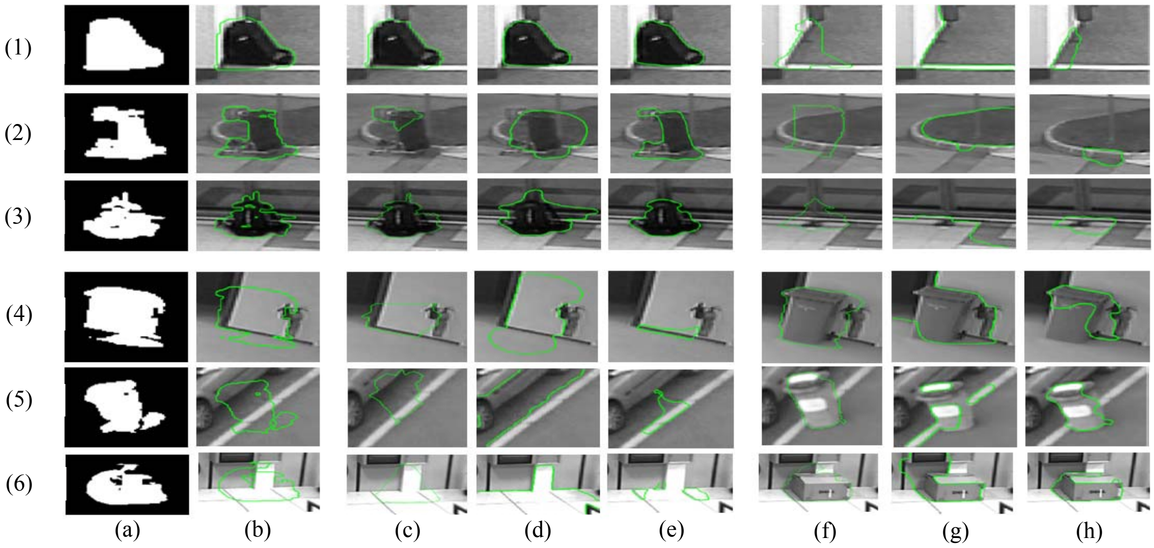

Figure 3: Real examples of abandoned (rows 1, 2 & 3) and stolen (rows 4, 5 & 6) objects. (a) Foreground mask, (b) initial contour and its adjustment in current frame ((c) PE, (d) GR and (e) GE) and background frame ((f) PE, (g) GR and (h) GE).

Table 4: S*cores obtained for real examples*

	PE			**GR**			**GE**			**ED**	**CH**
	d^F	d^B	s	d^F	d^B	s	d^F	d^B	s	s	s
(1)	0.90	0.66	0.24	0.84	0.31	0.52	0.84	0.33	0.50	0.82	-0.15
(2)	0.37	0.70	**-0.33**	0.62	0.37	0.24	0.85	0.31	0.54	0.52	-0.18
(3)	0.88	0.68	0.20	0.79	0.42	0.37	0.85	0.55	0.29	**0.22**	-0.34
(4)	0.65	0.88	-0.22	0.68	0.74	-0.05	0.17	0.63	-0.46	0.29	0.15
(5)	0.70	0.82	-0.12	0.41	0.46	-0.05	0.36	0.80	-0.43	0	**-0.06**
(6)	0.75	0.90	-0.14	0.49	0.67	-0.17	0.27	0.80	-0.53	0.10	0.12

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