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BAYESIAN VISUAL TRACKING FOR INSPECTION OF UNDERSEA POWER AND TELECOMMUNICATION CABLES

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ABSTRACT

The surveillance and inspection of underwater installations such as power and telecommunication cables are currently carried out by trained operators who, from the surface, guide a Remotely Operated Vehicle (ROV) with cameras mounted over it. This manual visual control is, however, a very tedious job that tends to fail if the operator looses concentration. This paper describes a tracking system for underwater cables whose main objective is to allow an Autonomous Underwater Vehicle (AUV) to video-document the whole length of a cable. The approach is based on Particle Filters (PF) because of their natural ability to model multi-dimensional multi-modal probability density functions, what allows handling in a more appropriate way the ambiguities which naturally arise from undersea environments. Extensive experimental results over a test set of more than 10,000 off-line frames, for which a ground truth has been manually generated, have shown the usefulness of the solution proposed. All those images come from inspection runs captured by ROVs navigating over real power and telecommunication undersea cables. Besides, on-line results obtained from an unmanned vehicle guided by the cable tracker in a water tank are also available and are discussed in the paper.

Keywords: Autonomous Underwater Vehicles, Robot Vision, Cable Tracking, Bayesian Tracking, Particle Filter.

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INTRODUCTION

Due to the particularly aggressive conditions to which undersea cables are exposed, the feasibility of such installations can only be guaranteed by means of a suitable inspection programme. It must provide timely information on the current state of the installation or about potentially hazardous situations or damages caused by the mobility of the seabed, corrosion, or human activities such as marine traffic or fishing (Iovenitti et al., 1994; Whitcomb, 2000).

Inshore, divers can take care of part of the maintenance programme, but offshore —with increasing depth— *Unmanned Underwater Vehicles* (UUV) are preferably used. In such a case, the surveillance and inspection tasks are carried out using video cameras attached to *Remotely Operated Vehicles* (ROV) which must be steered by well-trained operators in a support ship. Such a manual visual control is a very tedious job and tends to fail if the operator looses concentration. Besides, undersea images possess some peculiar characteristics which increase the complexity of the operation: blurring, low contrast, non-uniform illumination and lack of stability due to the motion of the vehicle, to name but a few. Moreover, ROVs are connected to the support vessel by means of an umbilical cable which, on the one hand, requires a *Tether Management System* (TMS) and, on the other hand, due to its rigidity and floatability, limits the maneouverability of the vehicle as well as its working area. Therefore, the automation of any part of this process can constitute an important improvement in the maintenance of this kind of installations, with direct impact on the reduction of the number of errors, task execution time and monetary costs.

Apart from other solutions based on other sensors (e.g. acoustic), one form of automation based on vision cameras is the mere recording on video of the whole length of the cable, followed by the off-line analysis of the images acquired. A more sophisticated solution would also include a defect detection module, which would prevent the system from recording those frames in which the cable appears in good condition. In any case, in order to video-document the cable, the AUV control architecture must command the vehicle so as to let it fly over the cable, what leads to the tracking, frame by frame, of the pose (i.e. the position and the orientation) of the cable, in order to confine it within the *field of view* (FOV) of the camera during the mission. Thanks to the special visual features that artificial objects present, which allow distinguishing them in natural scenarios such as the seabed even in very noisy images, the automatic guidance of an AUV for such maintenance/inspection tasks by means of visual feedback turns out to be feasible. However, distracting background, such as rocks or algae growing on top and nearby cables, complicate the detection and tracking. Besides, ambiguities may occur when rocks or marine growth form shapes and textures that resemble a cable.

A novel tracking system for elongated structures, such as the aforementioned cables, was described in (Wirth et al., 2008). The approach was based on *Particle Fil-*

ters (PF) (Arulampalam et al., 2002; Isard and Blake, 1998) because of their natural ability to model multi-dimensional multi-modal probability density functions, what allows handling in a more appropriate way the aforementioned ambiguities. This property of PFs makes them of more general application than other popular stochastic approaches like the *Kalman Filter* and related variants (Chen, 2003; Ristic et al., 2004), although, as it is well known, at the expense of a larger computational cost.

This paper describes an evolution of the previous tracking system which allows considering different types of cables according to their visual appearance and presents an extensive set of experimental results which show the usefulness of the approach. More precisely, results for off-line processing of an extensive set of more than 10,000 images of real cables are provided. Since ground truth data have been manually generated for the image set, quantitative performance data for the cable tracker is available. Results of several experiments of autonomous cable tracking in a water tank by means of a UUV are as well available and are discussed in the experimental results section.

The paper is organized as follows: section 2 briefly enumerates other approaches for visually tracking undersea cables and pipes; section 3 describes in detail the particle filter-based approach; section 4 summarizes the most relevant results gathered so far about the performance of the tracker; and, finally, section 5 concludes the paper.

RELATED WORK

Several proposals can be found regarding visual cable and pipeline tracking and inspection. On the one hand, due to the line-like appearance of this type of installations, several groups have proposed trackers using essentially edge maps and the Hough transform: Matsumoto and Ito (Matsumoto and Ito, 1995) to follow power cables, Hallset (Hallset, 1996) to track a pipeline in a network of pipelines, and Balasuriya and Ura (Balasuriya and Ura, 1999) for telecommunication cables. On the other hand, Zingaretti et al. (Zingaretti et al., 1996) developed a system which detected underwater pipes and some other accessories attached to them using statistical information obtained from selected areas of the image. Rives and Borrelly stated the vehicle control problem as a visual servoing application and proposed a solution for it (Rives and Borrelly, 1997). Grau et al. (Grau et al., 1998) proposed an approach based on texture descriptors learnt from the appearance of the cable and the background in a previous stage. Ortiz et al. proposal involves, due to the complexity of the images to be processed, a first step of image segmentation followed by a second step where the cable sides were reconstructed from the contours of the resulting regions (Ortiz et al., 2002; Antich and Ortiz, 2003). Asif and Arshad (Asif and Arshad, 2006), in a similar way, also proposed, through a quite complex algorithm, a cable sides reconstruction step after the detection of image edges. More recently, Inzartsev and Pavin presented a tracker for narrow cables mixing an algorithm for detecting the longest straight line on the current image and the use of electromagnetic sensors to improve the tracking performance (Inzartsev and Pavin, 2008).

THE PARTICLE FILTER

PFs approximate probability density functions by a set of N weighted *particles*, the sample set $S = \{(s^{(i)}, \pi^{(i)}) \mid i = 1,\ldots,N\}$. Each particle represents a particular (hypothetical) configuration s of the variables (i.e. one state) in the state space, together with an importance weight π, where the *state model* and the *state space* must be chosen for the given application. The evolution of the sample set is defined by two models: the *movement model*, which defines how the particles are moved in state space from one time step to the next, and the *observation model*, which is used to weight the particles according to a given observation (e.g. a camera image). The adequate combination of all these models within the particle filter paradigm allows estimating sequentially the likelihood of the cable pose: i.e. for every frame in the video sequence, the previously computed probability density function of the cable parameters is used to predict —via application of the movement model— the cable pose in the next frame; subsequently, the probability density function is updated by means of the observation model; the most appropriate cable pose estimate is finally determined from the resulting density. The following sections describe in detail the different models adopted for the cable tracker here described.

Cable Model

Figure 1(b) illustrates the model chosen for the undersea cable as it appears in camera images (see figure 1(a) for an example), while the state components are enumerated in table 1. As can be observed, the cable is modeled by two bi-dimensional straight lines separated by the apparent width the cable shows in the images, what implicitly assumes the cable does not exhibit an appreciable curvature in the images because of its rigidity or due to the distance to the sea bottom at which the vehicle navigates. While tracking a cable, the underwater vehicle is supposed to navigate at a constant distance to the seabed. Therefore, the vehicle only changes its yaw angle and performs longitudinal translations, being its movements confined within a 2D plane parallel to the ground.

In case of narrow cables, such as the ones used in telecommunications, the cable model can be further simplified to just one straight line, which would in general correspond to the cable main axis in the image. Such simplification is straightforward from the state model defined, just setting $w = 0$ and $\beta = 0$. In this way, the vehicle can be prevented from having to navigate extremely close to the seabed in order to "see" in the images a cable thick enough so as to allow the image processing algorithms to discriminate the two straight lines corresponding to the cable sides.

Several other benefits result from the adoption of this model for both thick and narrow cables:

— it allows avoiding or at least diminishing to an acceptable level the problem with suspended particles due to vehicle propellers when navigating close to the seabed;

— keeping constant the distance to the seabed is no longer critical provided the cable in the images can still be correctly modeled by a single line; and

— since the vehicle does not need to navigate close to the seabed, the part of the scene within the FOV of the camera enlarges, making more difficult to have the cable disappearing in the images.

(a) (b)

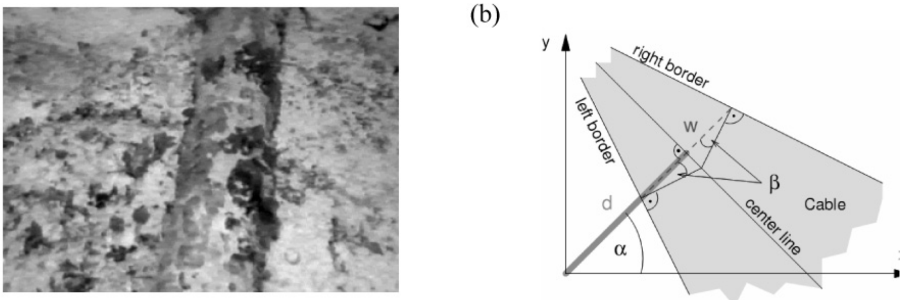

Figure 1: (a) Image of an undersea power cable. (b) Cable model (the coordinate system origin is at the center of the image).

Component	Description
d	Distance to cable centerline
α	Angle of cable centerline
w	Cable width
β	Cable skew

Table 1: Cable model components.

Movement Model

In accordance with the previous assumptions, the overall transition of a state $x = (d, \alpha, w, \beta)$ from time t to $t+1$ has been defined, by means of a constant velocity model for the cable distance and angle (Gustafsson et al., 2002), as:

$$x_{t+1}^{*} = x_{t}^{*} + (v_d, v_\alpha, \Delta w, \Delta\beta, \Delta v_d, \Delta v_\alpha)_t^{\mathrm{T}}, \tag{1}$$

where the cable state has been augmented with an instant rotation velocity v_α and an instant translation velocity v_d, so that $x^* = (d, \alpha, w, \beta, v_d, v_\alpha)$. In equation (1), Δv_d, Δv_α, Δw and $\Delta\beta$ account for unmeasured or unknown components in the state dynamics (accelerations in cable distance/angle or velocities/accelerations in cable width/skew). In this work, they all are assumed small and, thus, are modeled as Gaussian random noise. On the other hand, in case of tracking narrow cables, the state components relative to cable width and skew are removed or set permanently to 0, as indicated before.

At each time step, the sample state $s^{(i)}$ represented by each particle *(i)* is modified accordingly to the previous model:

$$s_{t+1}^{(i)} = s_t^{(i)} + (v_d^{(i)}, v_\alpha^{(i)}, 0,0,0,0)_t^{\mathrm{T}} + \left(\mathrm{G}(\sigma_d^2), \mathrm{G}(\sigma_\alpha^2), \mathrm{G}(\sigma_w^2), \mathrm{G}(\sigma_\beta^2), \mathrm{G}(\sigma_{vd}^2), \mathrm{G}(\sigma_{v\alpha}^2)\right)^{\mathrm{T}}, \quad (2)$$

where $\mathrm{G}(\sigma^2)$ represents Gaussian zero-mean random noise. In particle filters terminology, the addition of the instant velocities is called *drift* and the addition of the random noise is the *diffusion*.

This model assumes that the different state components are mutually independent, which does not need to be the case. However, the different experiments performed have shown that this simple uncoupled constant velocity model is precise enough to follow cable movements in real sequences, such as those coming from inspection runs captured by ROVs.

Observation Model

In order to determine the weight $\pi^{(i)}$ for particle *(i)*, the (hypothetical) cable pose for such particle is first projected onto the current frame. Next, the response of a suitable filter for all the image points lying along the projection is determined (the filter is oriented orthogonally to the projection). The particle is finally scored with the average of filter responses. Two filters have been considered (see figure 2(a)): the *derivative of Gaussian* (DoG) filter, typically used for estimating image gradient information, and the unidimensional *mexican-hat* function (MeX filter from now on):

$$\mathrm{DoG}(x) = -\frac{x}{\sigma^3\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \quad , \quad \mathrm{MeX}(x) = \left(1 - \frac{x^2}{\sigma^2}\right) e^{-\frac{x^2}{2\sigma^2}} \quad (3)$$

Figure 2(b) plots the respective filter responses for a 1D synthetic signal. As can be observed, the MeX filter emphasizes impulse-like signal changes with a larger response than the DoG filter, which tends to over-smooth such changes. On the other hand, the MeX filter produces a double response for step-like signal variations, while the DoG filter does not but emphasizes the step. Therefore, it must be expected better results from the MeX filter when tracking a cable which appears narrow in the images, while the DoG filter seems to be more appropriate for thick cables.

Finally, in order to speed up the calculation of particle weights, instead of using a filter oriented perpendicularly to each pose, horizontal and vertical mask filters are

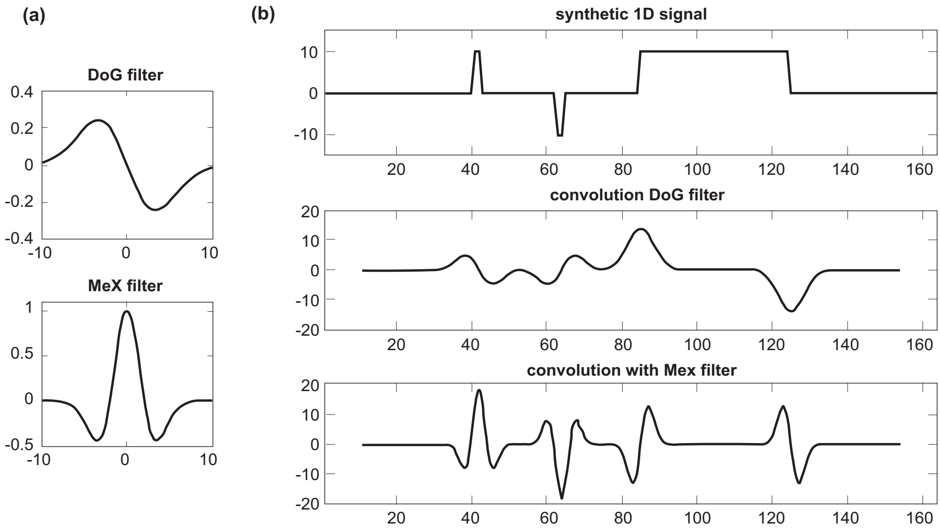

Figure 2: (a) Filters considered in the design of the observation model. (b) MeX and DoG ilter responses for a 1D synthetic signal.

defined and respective convolution images are computed for the current image. Oriented filter responses are then approximated for every particle *(i)* according to equation (4):

$$I_{\alpha^{(i)}} = \left(\cos\alpha^{(i)}\right) I_x + \left(\sin\alpha^{(i)}\right) I_y \ , \tag{4}$$

where I_x and I_y are, respectively, the "horizontal" and "vertical" response images.

Filter Initialization

In order for the tracker to follow the cable, the cable must first be detected so as to initialize the PF with a proper density. In this work, the PF is initialized in accordance with the results of analyzing selected rows and columns of the current frame. For such rows/columns, peaks in the Mex/DoG filter responses are located and the 1 or 2 largest magnitude peaks are kept depending on whether a narrow or a thick cable is tracked. Next, an initial particle set is generated by considering the lines joining every pair of selected peaks. If the image contains a cable, the best particle of the initial set can be expected to be scored very high (i.e. above a certain threshold) and coincide with the cable. In such a case, the cable is considered detected and the tracking starts; otherwise, the cable detection is considered unreliable, the image is discarded and the procedure is repeated with the next image. In such a case, the vehicle controller should not receive any motion order. Figure 3 illustrates this process for a narrow cable.

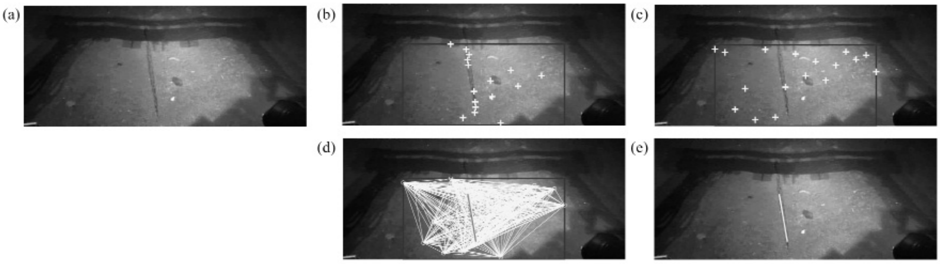

Figure 3: Illustration of the cable detection strategy: (a) original image; (b) crosses correspond to the maximum response of selected image rows; (c) crosses correspond to the maximum response of selected image columns; (d) particles generated (in yellow) and the best particle (in red); (e) best particle in yellow [The blue frame is a region of interest.].

EXPERIMENTAL RESULTS

An extensive set of experiments have been performed during the development of the cable tracker which has been described in this paper. A summary of results highlighting the most relevant facts about the tracker performance is presented in this section.

For a start, the tracker has been tested using a set of six video sequences of telecommunication cables and six video sequences of power cables. They all account for a total of around 150,000 images (approximately, one hour and a half of continuous video) and they all come from several sessions with an ROV navigating over real cables in a variety of situations: cables completely visible/partially hidden/totally hidden, uniform/cluttered background, scenes sufficiently/poorly illuminated, high/low contrast images, variations in the apparent thickness of the cable, etc. Figures 1(a) and 3(a) are examples of, respectively, the power (thick) and telecommunication (narrow) cables considered in these experiments. To obtain quantitative performance data, several excerpts representative of the previous sequences and com-

Excerpt	Number of frames	Average estimation error			
		Δd (pixels)	$\Delta\alpha$ (°)	Δw (pixels)	$\Delta\beta$ (°)
1	248	7.34	3.84	4.46	0.88
2	499	2.63	1.67	8.88	1.15
3	409	2.75	1.38	5.12	0.82
4	172	12.42	4.11	9.51	1.26
5	171	3.38	1.11	2.23	0.90
6	129	5.02	2.92	4.46	1.72
global average	1628	4.68	2.22	6.28	1.05

Table 2: Off-line processing results for thick cables.

Excerpt	Number of frames	Average estimation error	
		Δd (pixels)	$\Delta\alpha$ (°)
1	1400	6.44	3.41
2	500	1.79	0.88
3	4300	3.15	1.27
4	2600	4.34	0.96
5	900	3.42	1.26
6	600	9.37	1.92
global average	10300	4.21	1.50

Table 3: Off-line processing results for narrow cables.

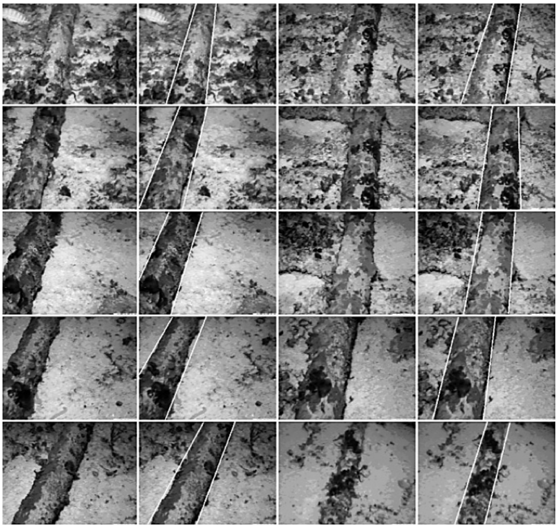

Figure 4: From top to bottom and left to right, tracking results for frames 1-225 of one of the power cable video sequences: ($1^{st}/3^{rd}$ columns) original frames; ($2^{nd}/4^{th}$ columns) processing results: yellow – cable estimate. (Every 25th frame is shown.)

prising more than 10,000 frames have been labelled with ground truth information. Performance has been measured by means of the average cable distance and angle errors with regard to the ground truth.

Apart from the off-line experiments, this section also provides results for a number of trials executed over a real vehicle navigating in a water tank.

In all the experiments, the filter handled sets of 500 particles and the Gaussian noise variances were determined experimentally. The filters used within the observation model made use of 21 pixel 1D masks. Finally, the state estimators used in the off-line and the on-line experiments were, respectively, the weighted average of the 5% best particles and the best particle.

Results of Off-line Experiments

Results for thick cables can be found in table 2, while table 3 provides results for narrow cables. As can be observed, on average, the error is of the order of 3-5 pixels for the cable distance and 1-2 degrees for the cable angle, what proves the usefulness of the approach. Additionally, a set of video sequences accounting for almost 150,000 frames and around 90 minutes of continuous video have been successfully processed. A sample of the results obtained for thick and narrow cables can be seen in, respectively, figures 4 and 5.

Results of On-line Experiments

Apart from the off-line experiments described in the previous section, the cable tracker has been tested along a number of trials with the ROV of figure 6. It is a small programmable ROV fitted with a compass, a depth sensor and a colour camera. The reduced size of this vehicle allowed us to perform the experiment in a 7.35m × 3.75m × 1.32m water tank. To carry out this experiment, the visual tracker was integrated with a subset of the control architecture described in (Antich and Ortiz, 2005).

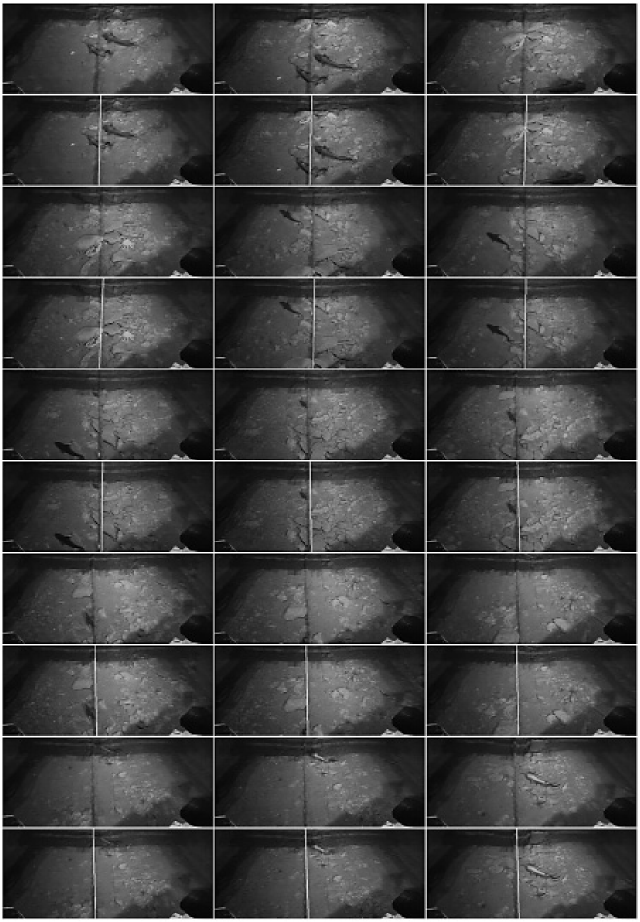

Figure 5: From left to right and top to bottom, tracking results for frames 20,800-21,450 of one of the telecommunication cable video sequences: (odd rows) original frames; (even rows) processing results: yellow-cable estimate (Every 50th frame is shown).

Figure 6: Nautilus microROV (from Albatros Marine Technologies).

Briefly speaking, those components of the architecture related with sensors not available in the experimental platform were deactivated.

Due to lack of space, figure 7 plots results for only two of the different trials that were performed. Each trial consisted in, without any human intervention, tracking the cable along four runs of the water tank, so that the vehicle had to turn autonomously at the end of every run. At the beginning of every run, the tracker had, thus, to look for the cable during the so-called *sweeping* stage, along which the vehicle performed a zigzag movement to sweep the tank in search for the cable. In order for the *sweeping* stage to last longer, the tracker was programmed so as to ignore the cable during the 2-3 first sweeping lines of the stage. Positioning information was available thanks to a visual positioning pattern at the bottom of the water tank. Table 4 provides quantitative performance results in the form of horizontal separation between the vehicle and the cable, to observe the capability of the tracker for making the vehicle "fly" over the cable. As can be observed, the vehicle did not detach from the cable more than 12 cm on average, and never more than about 40 cm.

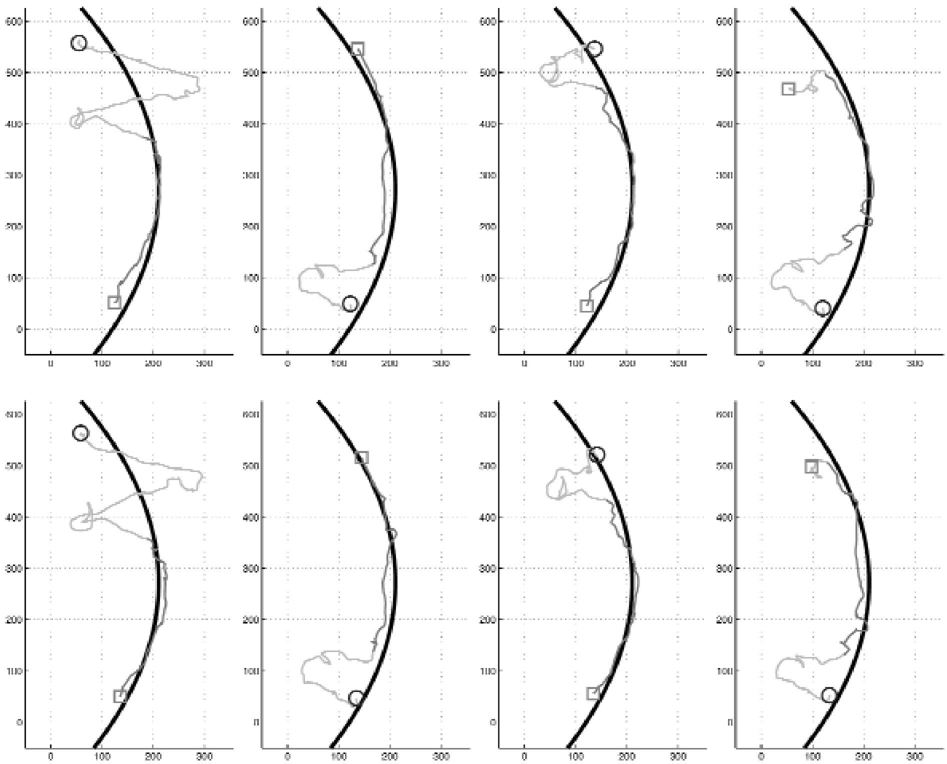

Figure 7: Paths followed by the vehicle during two trials (respectively, upper and lower rows) of a multiple-run experiment: the blue circle represents the position of departure while the magenta square indicates the end of the path; the sweeping and tracking stages are indicated in, respectively, green and red; from left to right, first, second, third and fourth runs of the trial; the thick black line is the cable at their real location.

	1st run	2nd run	3rd run	4th run	all runs
no. frames	127	149	159	139	574
AAD (cm)	10.16	15.92	10.69	12.56	12.38
MAD (cm)	35.94	32.94	34.77	41.31	41.31

	1st run	2nd run	3rd run	4th run	all runs
no. frames	133	146	137	157	573
AAD (cm)	9.27	12.39	9.74	14.70	11.66
MAD (cm)	19.26	30.26	24.27	38.60	38.60

Table 4: Tracking results for two trials (respectively, upper and lower tables): difference between vehicle and cable horizontal positions (tracking stage), AAD=Average Absolute Difference, MAD=Maximum Absolute Difference.

CONCLUSIONS

Extensive experimental results over a test set of more than 10,000 frames, for which ground truth data have been manually generated, have shown the usefulness of the cable tracking solution proposed.

Quantitative performance data in this regard has been gathered, yielding a global error for the cable tracker of, on average, between 4 and 5 pixels for the cable distance and between 1 and 2 degrees for the cable angle, what proves the usefulness of the approach. A set of video sequences accounting for almost 150,000 frames and around 90 minutes of continuous video have also been successfully processed. Besides, the cable tracker has been tested over a real vehicle in a water tank, yielding similar performance.

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SEGUIMIENTO VISUAL BAYESIANO PARA LA INSPECCIÓN DE CABLES DE POTENCIA Y DE TELECOMUNICACIONES SUMERGIDOS

RESUMEN

La operabilidad de una instalación submarina consistente en cables de transporte de energía eléctrica o de telecomunicaciones puede sólo ser garantizada a través de un programa de inspección capaz de proporcionar a tiempo información sobre condiciones de peligro potenciales o daños causados por la movilidad del suelo oceánico, la corrosión o actividades humanas tales como el tráfico marino y la pesca.

Hoy en día, estas tareas de vigilancia e inspección son realizadas por operadores que desde la superficie de un barco controlan un *vehículo operado remotamente* (ROV) sobre el que se han montado cámaras de vídeo. Evidentemente, ésta es una tarea tediosa en la que el operador debe permanecer largos periodos de tiempo concentrado frente a una consola, favoreciendo todo ello la aparición de errores cuyo origen es, principalmente, la pérdida de atención y la fatiga. Además, las peculiares características de las imágenes obtenidas del fondo marino —zonas difuminadas, bajo contraste, iluminación no uniforme, etc.— dificultan aún más la ya compleja operación. Por tanto, la automatización de cualquier parte de este proceso puede constituir una importante mejora en el mantenimiento de este tipo de instalaciones, no sólo en cuanto a la reducción del tiempo de inspección y de los errores, sino también de los costes asociados.

Con este objetivo, se propone un sistema visual de seguimiento de estructuras elongadas sumergidas capaz de proporcionar las consignas adecuadas para realizar el guiado de un *vehículo autónomo submarino*, de forma que a lo largo del guiado se pueda registrar en vídeo la estructura inspeccionada. La solución propuesta en este artículo se basa en los denominados *filtros de partículas* debido a su facilidad natural para modelizar funciones de densidad de probabilidad multi-dimensionales y multimodales, lo cual permite gestionar de forma más apropiada las ambigüedades que típicamente resultan de entornos no estructurados como el lecho marino. Esta propiedad de los filtros de partículas les permite abarcar un rango mayor de aplicaciones que otras soluciones como los Filtros de Kalman y sus variantes, aunque, como es bien conocido, a costa de un mayor coste computacional.

Los filtros de partículas aproximan funciones de densidad de probabilidad mediante conjuntos de *partículas* $S = \{(s^{(i)}, \pi^{(i)}) \mid i = 1,\ldots,N\}$. Cada *partícula* representa una particular (e hipotética) configuración s de variables (esto es, un estado) en el espacio de estados, al cual se le asocia un peso o importancia π; el modelo de estado, junto con el espacio de estados, se escoge para cada aplicación. La evolución del conjunto de partículas viene definido por dos modelos: el *modelo de movimiento*, que

define cómo se desplazan las partículas dentro del espacio de estados de un instante al siguiente, y un *modelo de observación*, el cual pondera las partículas de acuerdo con la observación actual (p.e. la imagen actual). La combinación adecuada de estos tres modelos a través del paradigma del filtro de partículas permite estimar secuencialmente la verosimilitud del estado del cable: para cada imagen de la secuencia, la función de densidad de probabilidad previamente estimada es utilizada para predecir —a través de la aplicación del modelo de movimiento— el estado del cable en la siguiente imagen; a continuación, la función de densidad de probabilidad es actualizada mediante la observación actual y el modelo de observación; el estado más probable del cable es finalmente determinado a partir de la densidad de probabilidad resultante.

En el artículo se describen los diferentes modelos utilizados en la solución actual, donde: el cable es modelizado por una o dos líneas rectas, dependiendo de su grosor aparente en las imágenes, el modelo de movimiento asume velocidad aproximadamente constante y el modelo de observación se define en base a la respuesta de un filtro de imagen especialmente adaptado para el tipo de cable a seguir.

CONCLUSIONES

La extensa colección de resultados experimentales presentados en este artículo, correspondientes a un conjunto de test de más de 10.000 imágenes etiquetadas manualmente con la detección correcta del cable que en ellas aparece, muestran la utilidad de la estrategia de seguimiento de cables sumergidos que se ha propuesto. En particular, a nivel cuantitativo, los experimentos realizados en cuanto a procesamiento de imágenes derivan en un error de, en promedio, entre 4 y 5 píxeles para la posición del cable, y 1-2 grados para la orientación del cable. Adicionalmente, un conjunto de secuencias de vídeo que comprenden casi 150.000 imágenes y alrededor de 90 minutos de vídeo continuo ha sido igualmente procesado con éxito. Finalmente, el seguidor de cables ha sido verificado en un tanque de agua con un vehículo submarino no tripulado, obteniendo un rendimiento igualmente satisfactorio.