Interactive Segmentation of Objects in Images and Videos using Graphs and Fuzzy Models of Content Knowledge

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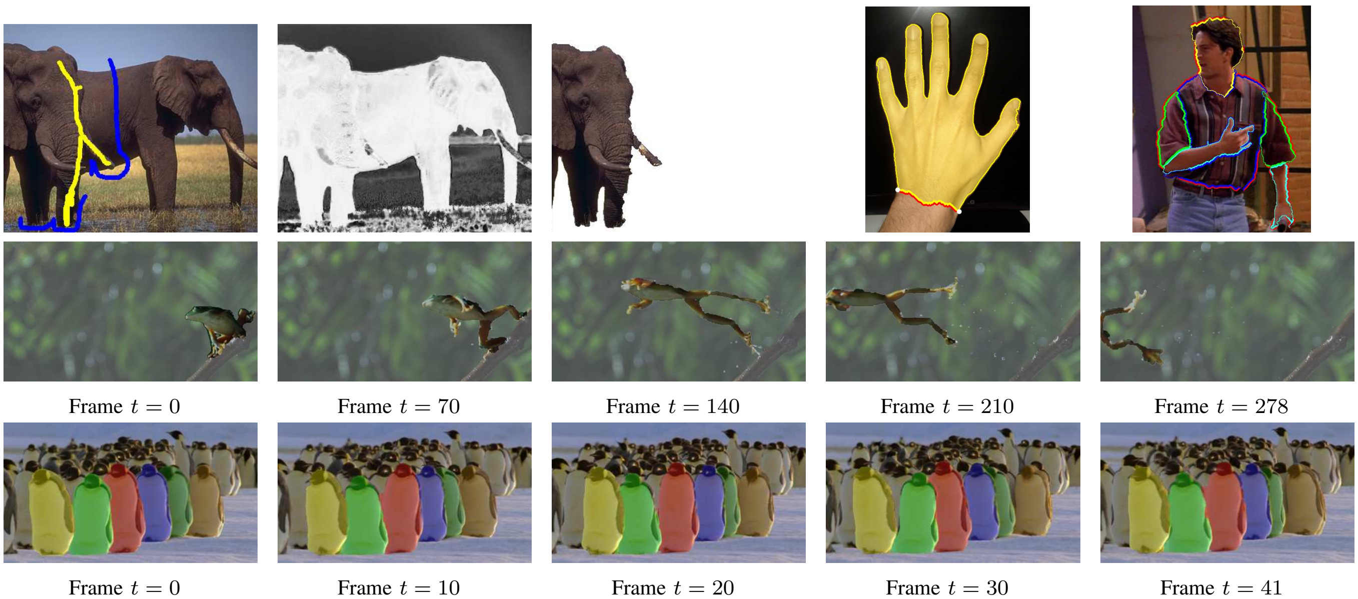


Fig. 1. **Top row**: graph-based interactive image segmentation using intelligent arc-weight estimation (first three images) and the LiveMarkers paradigm for single and multi-object segmentation (next two images). **Middle and bottom rows**: interactive video segmentation results using FOMTrace to separate foreground and background with overlapping color distributions and to delineate multiple objects simultaneously, respectively.

***Abstract*—Interactive segmentation is often necessary for image and video editing applications, which demand for effective and efficient methods capable of aiding the user to accurately extract objects of interest from the background with minimum involvement. The main goal is to place those objects on to new target images and videos, thereby avoiding the need to use green screens to acquire the footage. In this PhD research, we have devised methods that may be used by amateurs and professionals alike for interactive image and video segmentation, aiming to minimize the user's effort and time required to obtain an accurate result. In particular, we have developed two methods for interactive image segmentation, and one for interactive video segmentation that outperforms/competes with a state-of-the-art commercial software. Our methods have also aided in interdisciplinary research with Geology, Psychology/Psychiatry (body pose estimation for early Autism assessment), and 3D medical imaging.**

I. Introduction

In recent years,[1] regular users have changed from mere consumers to active producers of multimedia data commonly shared in the social networks [1]. In this scenario, photo and video editing are core tasks to many applications (e.g., Snapshat and PhotoGrid), which very often call for object segmentation. Image and video object segmentation aim to separate from the background the set of pixels perceived as belonging to the foreground (Figure 1). Those objects may be further enhanced with digital filters and matte onto other images and videos (Figure 2). Segmentation is also an important pre-processing step for problems such as body pose estimation [2], human action recognition [3], sedimentary petrography [4], and remote sensing [5]. The broad definition of foreground and background in natural scenes makes very hard to develop automatic algorithms to separate them.

User intervention is therefore necessary when the spatial extent of objects in images and videos must be accurately defined. Interactive image segmentation techniques usually exploit the synergism between user-provided foreground location and computer-based foreground delineation, in order to increase effectiveness [6], [7]. Humans are capable of locating the object in an image with a few mouse clicks (Figure 2) and

[1]Ph.D. research conducted between March 2010 and September 2015.

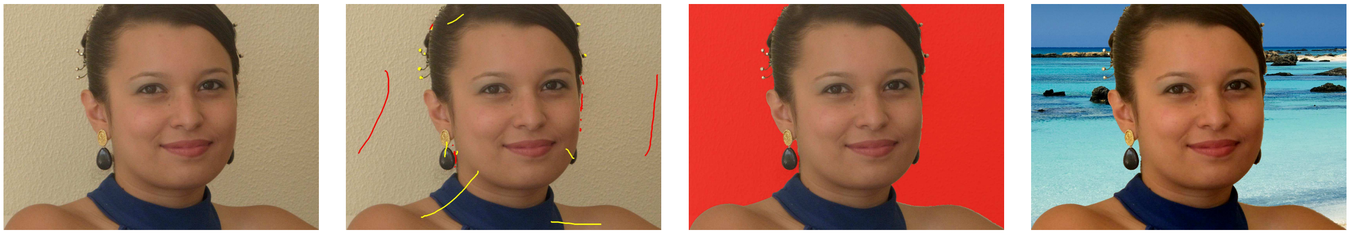


Fig. 2. Interactive image segmentation with user-drawn scribbles to solve foreground location, applied to *matte* the foreground with a new background.

pointing out delineation errors, while the machine is better equipped to precisely delineate objects, even if inaccurately. A bad alternative would be the complete manual delineation of the foreground, a cumbersome and impractical procedure in any setting. Moreover, image and video segmentation is an intrinsically ill-posed problem, requiring the user to resolve ambiguities when connected parts of the foreground and the background share similar properties (Figure 3). Those problems further escalate in interactive video segmentation, since each frame is an image that must be delineated with temporal coherence [8], [9] (e.g., Figure 5).

Segmentation is particularly challenging because the computer must fill in the semantic gap between the user's knowledge about the object of interest and the raw input data (image pixels and video frames). This difficulty makes interactive segmentation not a single shot task. It requires the user to draw a set of scribbles to locate the object for the computer to perform a first delineation. Then, the user must verify if the result is correct and add more scribbles when errors occur. This is an iterative process that may heavily burden the user, who may even have to delete markers that were inadvertently misplaced due to fatigue and/or carelessness. This is particularly troublesome in video segmentation, since the objects are dynamic and may change in shape, topology, and even color/texture from one frame to another. Those issues lead to the following questions: i) how do we incorporate a minimum of the user's knowledge about the object of interest for image segmentation? ii) how do we propagate that information to the remaining pixels? iii) how do we build more complete models of that knowledge from accepted segmentations? and iv) how do we minimize the user's effort without loosing his/her control over the process?

This PhD research [10] sought to answer the above questions, by interpreting images and videos as weighted graphs in which the sparsely annotated information (user-drawn scribbles in images and segmented frames in video) could be propagated to the unlabeled data. In images, we studied arc-weight estimation techniques to facilitate propagation, and strategies to enhance user interaction for error correction. In video, we constructed object shape knowledge models from the user-segmented frames that automatically correct the propagated segmentation across time to minimize the need of further user intervention. We briefly describe those contributions next, along with results obtained for studies in 3D medical imaging, Geology, and early Autism assessment research. We then present a list of publications in Section III resulting from this research, as well as a summary of awards and press coverage in Section IV, before stating our conclusions in Section V.

II. Scientific Contributions

A. Intelligent Arc-Weight Estimation for Interactive Image Segmentation

A natural way of exploiting the connectivity between the scribble pixels and the unannotated ones for propagating the object information is to make direct/indirect use of some image-graph concepts, such as arc weight between pixels [11]. The weight may represent attribute functionals such as similarity, speed function, affinity, cost, and distance; depending on different frameworks used for delineation, such as watershed [12], random walks [13], laplacian coordinates [14], level sets [15], fuzzy connectedness [16], graph cuts [17], and optimum path forests [18]. The effectiveness of segmentation in all of those frameworks is due to the quality of such arc-weight estimation, which can exploit local image properties and/or global object information (Figure 3).

In several methods [17], [19], [20], [13], [11], global object information is obtained from the user-drawn scribbles. They learn a pattern classifier from the foreground and background labeled pixels aiming to enhance those differences (Figures 3a-c). Although this is critical for segmentation and works well when the foreground has significantly different colors from the background, when the color distributions overlap (i.e., if we are interested only in the first zebra in Figure 3), such an estimation fails if all scribble pixels are used for training (Figures 3d-e). Some pixels of the drawn markers represent different image properties, useful to distinguish object and background, for improving arc-weight estimation. However, their automatic identification is challenging during delineation. Some approaches have even proposed to perform interactive arc-weight estimation in a prior step [11], to prevent careless re-estimation that drops performance and reduces user control [19], [17], [20], [13].

We have proposed in [21] an intelligent way to select only the best scribble pixels for arc-weight estimation transparently to the user, aiming to provide high quality arc weights that facilitate segmentation with minimum user effort (Figures 3d and 3f). The basic idea is to cluster all of the image pixels and to select for object enhancement via pattern classification only the foreground and background seed pixels that fall in distinct clusters. Then, the final delineation considers all seed

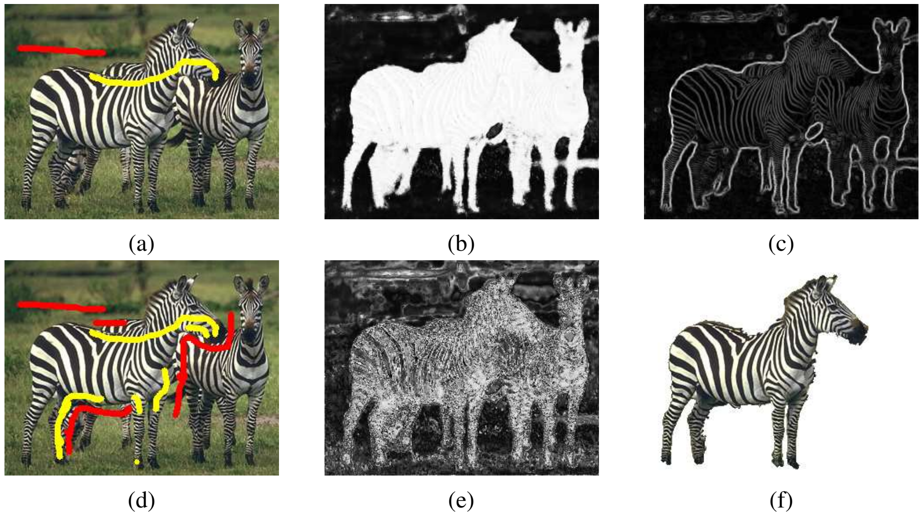


Fig. 3. (a) Initial scribbles created by the user. (b) Object enhancement map obtained through pattern classification. (c) Gradient image where brighter regions represent higher arc weights. (d) New set of markers selected for image segmentation. (f) The new set of markers selected for object delineation yields poor classification and arc-weight estimation if used entirely for training. (e) Delineation result with our intelligent method using directly the scribbles from (d).

pixels (Figure 3f). We have also proposed a procedure to determine when and where the weights can be recomputed to increase accuracy without loss of user control. This work resulted in an award wining conference paper and an invited journal publication (Section IV).

B. Interactive Image Segmentation using Live Markers

In spite of our best efforts, arc-weight estimation may still fail for complex situations. We must guarantee in those cases that the user is still able to accurately fix delineation errors with minimum effort. In this sense, in scribble-based image segmentation methods derived from several frameworks [18], [16], [12], most error correction occurs near the object's border (Figures 4a-c), in places with little boundary evidence due to arc-weight estimation being unable to increase the contrast between foreground and background. Those are critical locations that call for careful placement of scribbles (markers) to protect foreground and background from leaks in segmentation. This is often hard to be achieved by the user with scribbles, thereby requiring more time and attention.

At the same time, boundary-tracking techniques [22], [23] provide a different form of user interaction for image segmentation. Instead of adding scribbles, the user adds *anchor* points near the object's boundary and guides the computer in the selection of boundary segments that divide foreground and background (Figure 4b). Scribble- and anchor point-based image segmentation paradigms have complementary strengths and weaknesses that can be addressed to improve the interactive experience by reducing the user's effort. We have proposed in [7] a hybrid paradigm based on a form of interaction called *live markers*, in which optimum boundary-tracking segments are turned into internal and external markers for region-based delineation to effectively extract the object (Figures 1 and 4).

We proposed four techniques within this paradigm: LiveMarkers, RiverCut, LiveCut, and RiverMarkers. The homonym LiveMarkers couples boundary-tracking via *live-wire-on-the-fly* [22] (LWOF) with optimum seed competition by the *Image Foresting Transform* [18] (IFT-SC). The IFT-SC can cope with complex object silhouettes, but presents a leaking problem on weaker parts of the boundary that is solved by the effective live markers produced by LWOF. Conversely, in RiverCut the long boundary segments computed by Riverbed [23] around complex shapes provide markers for Graph Cuts by the Min-Cut/Max-Flow algorithm [17] (GCMF) to complete segmentation on poorly defined sections of the object's border, thereby avoiding GCMF's well known shrinking bias. LiveCut and RiverMarkers further demonstrated that live markers can improve segmentation even when the combined approaches are not complementary. Moreover, since delineation is always region-based, our methodology subsumes both paradigms, representing a new way of extending boundary-tracking to the 3D image domain (Figures 4d-e), while speeding up the addition of markers close to the object's boundary.

C. Interactive Video Segmentation using FOMTrace

In video segmentation, besides the challenges present in image segmentation such as high color overlap between foreground and background, the developed techniques must also handle fast-moving and deformable objects, simultaneous segmentation of multiple objects, possible occlusions, topology changes, among others. Therefore, instead of requiring the user to apply the aforementioned interactive image segmentation tools for every frame, we have proposed in [24] an interactive video segmentation method, named *FOMTrace*, which addresses the problem in an effective and efficient way.

From a user-provided object mask in a first frame (Figure 5a), our method performs automatic video segmentation on a spatiotemporal superpixel-graph, and then estimates a

Fig. 4. (a) Initial segmentation using scribbles. (b) Activation of boundary-tracking with one anchor point, and optimum path (yellow line) computed until the current cursor position (white cross). (c) Automatically generated live marker with internal and external seeds from the border segment and updated delineation. (d)-(e) 3D brain image segmentation result using LiveMarkers.

Fuzzy Object Model (FOM) that refines segmentation of the second frame, by constraining delineation on a pixel-graph within a region where the object's boundary is expected to be. The propagation of segmentation makes use of the same graph-based techniques we applied in the image case, but using the object mask to annotate superpixels instead of considering only the information provided by the user-drawn scribbles. The FOM incorporates the user's higher level knowledge about the object's shape, learned from the object mask, to preemptively correct errors in the propagated delineation from the previous frame. The user can accept the refined object mask in the second frame or correct it with our image tools, which is then similarly used to improve the spatiotemporal video segmentation of the remaining frames (Figure 5b-e). Both steps are repeated interchangeably, within interactive response times, until the segmentation refinement of the final frame is accepted by the user. FOMTrace has achieved superior or competitive results when compared with state-of-the-art approaches for interactive video segmentation, supervised and unsupervised object tracking, the first corresponding to the primary tool of a commercial software [24] (Adobe After Effects).

D. Secondary Applications

Segmentation of sandstone grain images: Segmentation is paramount for measuring sandstone grain properties such as roundness and sphericity, which allow us to infer about provenance and transport in sedimentary petrography. We have devised a pipeline in [4] to segment sandstone grain images, consisting of an automatic step in which the grains are separated first from the background and then from each other, a key novelty with respect to the literature, followed by interactive corrections wherever necessary using LiveMarkers (Figure 6).

Body pose estimation in video for early Autism assessment: Autism Spectrum Disorder (ASD) affects millions of people worldwide. Early intervention, initiated in preschool and sustained for at least 2 years, can substantially improve child outcome, specially if done before the full set of behavioral symptoms appears [25]. In spite of this, the average diagnosis age in the U.S. is of 5 years, given the lack of specialists to offer these assessments to the very young. The PhD research carried out during a sandwich period at the University of Minnesota, USA, aimed to develop computer vision tools that could aid general practitioners in the future in early detection of ASD signs, for faster diagnosis by expert clinicians. In particular, we have developed a facial tracking method in video, to estimate attention and gaze, and a body pose estimation technique to evaluate atypical motor patterns, such as asymmetrical arm positioning in unsupported gait of toddlers. The latter is an extension of our FOMTrace video segmentation method (Figure 7).

III. Scientific Dissemination of our Results

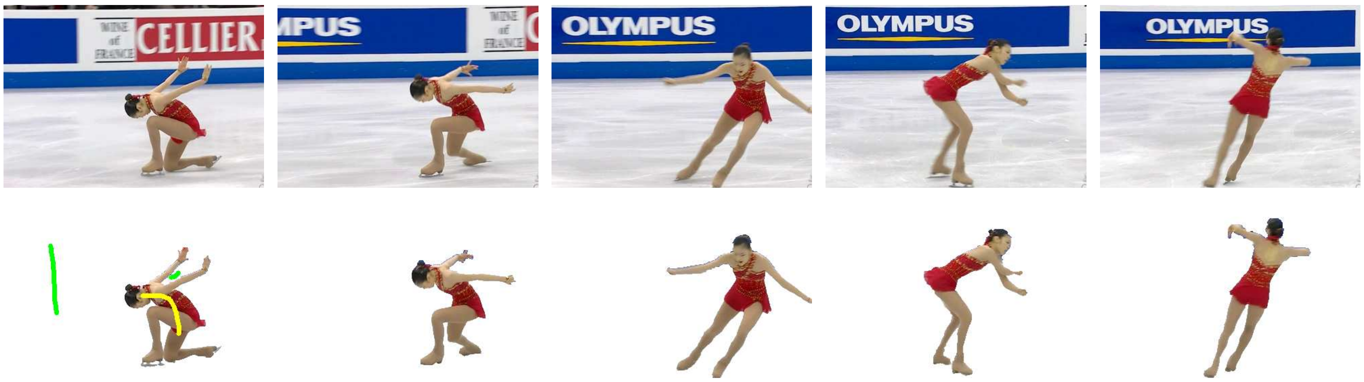
During the course of the PhD research, a total of 6 peer-reviewed journal papers and 7 conference papers were published in high quality avenues. The publications include three journals with Qualis A1 (two of which with Impact Factor above 3.6), one with Qualis A2, one with Qualis B1, and one open access journal from Psychology/Psychiatry. For greater details, please refer to the list of publications below, which includes supplementary works such as technical reports and awarded conference abstract/posters.

A. Published peer-reviewed journal papers

1) Spina, T. V., Miranda, P. A. V., and Falcão, A. X. (2014). Hybrid approaches for interactive image segmentation using the Live Markers paradigm. *IEEE Trans. Image Process.*. **Imp. factor: 3.625. Qualis A1.**
2) Hashemi, J., Tepper, M., Spina, T. V., Esler, A., Morellas, V., Papanikolopoulos, N., Egger, H., Dawson, G., and Sapiro, G. (2014). Computer vision tools for low-cost and noninvasive measurement of autism-related behaviors in infants. *Aut. Res. Treat.*
3) Mingireanov, I. F., Spina, T. V., Falcão, A. X., and Vidal, A. (2013). Segmentation of sandstone thin section images with separation of touching grains using optimum path forest operators. *Comput. Geosci.*. **Imp. factor: 2.054. Qualis A2.**
4) Minetto, R., Spina, T. V., Falcão, A. X., Leite, N. J., Papa, J. P., and Stolfi, J. (2012). IFTrace: Video segmentation of deformable objects using the Image Foresting Transform. *Comput. Vis. Image Underst.*. **Imp. factor: 1.540. Qualis A1.**
5) Miranda, P. A. V., Falcão, A. X., and Spina, T. V. (2012). Riverbed: A novel user-steered image segmentation method based on optimum boundary tracking. *IEEE Trans. Image Process.*. **Imp. factor: 3.625. Qualis A1.**
6) Spina, T. V., Miranda, P. A. V., and Falcão, A. X. (2012b). Intelligent understanding of user interaction in image segmentation. *Intl J. Pat. Recog. Artif. Intelli.*. **Imp. factor: 0.669. Qualis B1.**

B. Published peer-reviewed conference papers

1) Falcão, A. X., Spina, T. V., Martins, S. B., and Phellan, R. (2015). Medical image segmentation using object shape models:



Frame $t = 0$ Frame $t = 8$ Frame $t = 15$ Frame $t = 22$ Frame $t = 29$

Fig. 5. FOMTrace segmentation result of the video of a fast-moving figure skater on the top row, after interactive initialization in the first frame ($t = 0$).

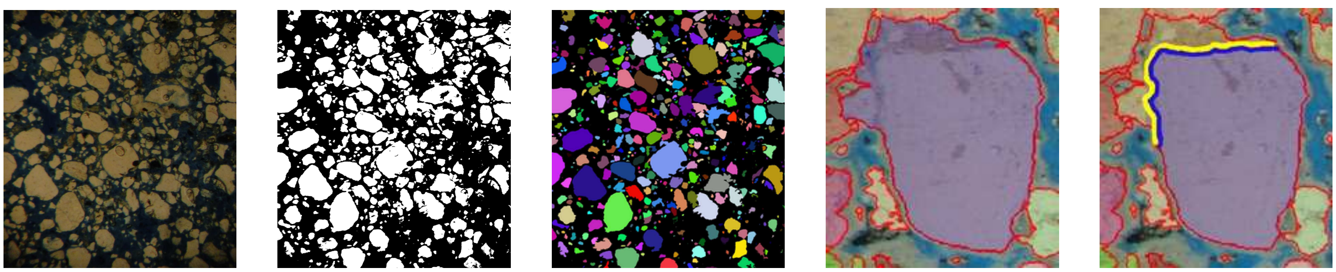


Fig. 6. Automatic sandstone grain segmentation with interactive correction.

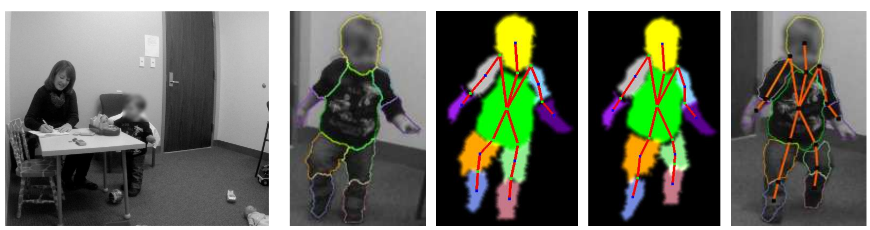


Fig. 7. Body pose estimation in video using Fuzzy Object Models. The third and fourth images depict our object shape model representing the human body, which is closely related to the one in FOMTrace.

A critical review on recent trends, and alternative directions. In *Computational Vision and Medical Image Processing*.

2) Spina, T. V. and Falcão, A. X. (2014). Robot users for the evaluation of boundary-tracking approaches in interactive image segmentation. In *ICIP*. **H5-index 38. Qualis A1.**
3) Rauber, P. E., Spina, T. V., Rezende, P., and Falcão, A. X. (2013). Interactive segmentation by image foresting transform on superpixel graphs. In *SIBGRAPI*.**H5-index 13. Qualis B1.**
4) Hashemi, J., Spina, T. V., Tepper, M., Esler, A., Morellas, V., Papanikolopoulos, N., and Sapiro, G. (2012). A computer vision approach for the assessment of autism-related behavioral markers. In *ICDL-EpiRob*. **H5-index 18. Qualis B2.**
5) Spina, T. V., Falcão, A. X., and Miranda, P. A. V. (2011). User-steered image segmentation using live markers. In *CAIP*. **H5-index 12. Qualis B2.**
6) Miranda, P. A. V., Falcão, A. X., and Spina, T. V. (2011). The riverbed approach for user-steered image segmentation. In *ICIP*. **H5-index 38. Qualis A1.**
7) Spina, T. V. and Falcão, A. X. (2010). Intelligent understanding of user input applied to arc-weight estimation for graph-based foreground segmentation. In *SIBGRAPI*. **Honorable mention award. H5-index 13. Qualis B1.**

C. *Other publications*

1) Spina, T. V. and Falcão, A. X. (2016). FOMTrace: Interactive video segmentation by Image Graphs and Fuzzy Object Models. Technical report, CoRR – arXiv. https://arxiv.org/abs/1606.03369.
2) Spina, T. V., Tepper, M., Esler, A., Morellas, V., Papanikolopoulos, N., Falcão, A. X., and Sapiro, G. (2013). Video human segmentation using fuzzy object models and its application to body pose estimation of toddlers for behavior studies. Technical report, CoRR – arXiv. https://arxiv.org/abs/1305.6918.
3) Spina, T. V., Hashemi, J., Tepper, M., Esler, A., Morellas, V., Papanikolopoulous, N., Falcão, A. X., and Sapiro., G. (2012a). Segmentation and body pose estimation of toddlers at risk of autism using clouds. Human Activity and Vision Summer School (HAVSS). **Awarded poster.**

IV. Work Recognition

The PhD research has received two awards and press coverage both in Brazil and abroad. We list next the main articles released in Brazilian press and the received awards.

- **Awards**

1) Top 3 best poster award at the Human Activity and Vision Summer School (HAVSS 2012) for the work "Segmentation and Body Pose Estimation of Toddlers at Risk of Autism Using Clouds."
2) Honorable mention for the Best Student Paper Award at the 23rd Conference on Graphics, Patterns, and Images (SIBGRAPI 2010) for the paper entitled "Intelligent Understanding of User Input Applied to Arc-Weight Estimation for Graph-Based Foreground Segmentation."

- **Press Coverage**

1) "Quadro a quadro", by Jornal da Unicamp, Carlos Orsi, June 13–19, 2016.[2]
2) "Software ajuda a identificar autismo", by Agência Anhanguera, Correio Popular, August 11, 2014.[3]
3) "Software aumenta a precisão na triagem de crianças com autismo", by Elton Alisson, Agência FAPESP, 16 July, 2014.[4]
4) "A medida do autismo", by Roberta Machado, Correio Braziliense, Tecnologia, pg. 14, 02 June, 2014.

V. Conclusions

In this PhD research, we have devised methods for interactive image and video segmentation to aid applications for multimedia data editing. Our techniques focused on minimizing the amount of necessary user intervention to achieve accurate results in difficult situations. To this end, we have interpreted images and videos as weighted graphs to use graph-based image processing operators combined with object knowledge models. Our techniques have also been applied to interdisciplinary research with Geology (sandstone grain segmentation), Psychology/Psychiatry (early Autism assessment), and Medicine (3D medical image segmentation). We have published a total of 6 journal papers, 7 national and international conference papers, and two technical reports during this period. This work has also been awarded two conference prizes and has drawn significant press coverage.

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