A Survey of Sperm Detection Techniques in Microscopic Videos

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ABSTRACT

Computer Assisted Sperm Analysis (CASA) plays a crucial role in the diagnosis and treatment of male reproductive health. In recent years, with the development of computer industry, more and more effective algorithms and techniques have been applied in this field to help CASA obtain more objective and quantitative analysis results rapidly. As target detection is an important part in image processing which is the basic technique of CASA and also includes pre-processing, feature extraction and tracking, this survey comprehensively analyses studies focus on target detection in CASA since 1988.

CCS CONCEPTS

• **Computing methodologies**; • **Computer graphics**; • **Image manipulation**; • **Image processing**;

KEYWORDS

Computer assisted sperm analysis, computer vision, target detection, microscopic video

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1 INTRODUCTION

Resent research shows that one in six couples are known to have fertility problems, of which more than 30% are significantly associated with male infertility [1], and many of them refer to diagnostic semen analysis to find the cause. In-Vitro Fertilization (IVF) method is one of the most popular techniques in assisting couples with infertility problems. However, since embryologists and technicians may not be able to select sound sperm [2], the success rate of IVF is pretty low (about 30-40%). Therefore, sperm analysis and quality assessment are of great significance for the diagnosis and treatment of male infertility and play an important role in human infertility.

In 2010, the World Health Organization (WHO) published a sperm quality assessment report [3], and it divided the sperm motility into four categories. According to criterion used in the report, technicians can use microscopes to manually count sperms and evaluate the quality of sperm motility with elaborate standard protocols [4]. Hence, the common methods of sperm analysis infertility clinics and research laboratories are laborious and subjective [5]. From this perspective, quantifying the data, improving test accuracy and avoiding subjective influence is particularly useful.

In [6], a review on "using five CASA systems to evaluate a single (donor) sample" was introduced, which revealed the impact of errors on data due to the differences in operator expertise and sample handling. Similarly, the work of [7] compares the Sperm Quality Analyzer IIC variables with the CASA estimates. According to these two reviews, the CASA technique offers better objectivity and accuracy than traditional manual testing methods. Therefore, the introduction of CASA techniques into clinical laboratories should therefore help improve the implementation of laboratory standardization and quality control procedures. With the development of CASA technology, CASA estimates, which will be more mature and provide more help in quantitative diagnosis, CASA system will become one of the important means to diagnose infertility [8].

Sperm detection is the first step of CASA, and its accuracy directly determines the follow-up target tracking and the calculation of sperm motility parameters. After reviewing the existing relevant literatures and reviews, we found that most of the literatures and reviews do not focus on sperm target detection. For example, in the work of [9], it only compares some simple applications of image processing, and in [10], only video segmentation and detection of sperm are discussed. They do not introduce the target detection algorithm in detail, nor analyze the technical difficulties of the target detection algorithm. Therefore, in this survey report, we summarize the target detection algorithms in relevant literatures in the past

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30 years and discuss the difficulties and shortcomings of existing target detection algorithms.

The CASA system usually includes four parts: Mechanical stage, illumination, and optical systems, image acquisition, and software output measures [11].

Mechanical stage: Move the optical microscope to a preset plane to help achieve vertical autofocus.

Illumination and optical systems: The interchangeable visible spectrum broadband lighting (390-700nm) or narrow-band lighting obtained through filters are usually applied in CASA. Besides, pulse lighting (which can reduce the damage of ultraviolet rays to sperms) and fluorescent lighting (for detecting abnormal sperm) are also common in practical.

Image acquisition: The microscopic video of sperm is captured by a solid-state camera sensor (CCD or CMOS) in the hardware system. The speed of the camera shutter determines the time interval between consecutive frames, as well as the quality of the image in the video. The faster camera shutter speed benefits reducing the gap between detected and real sperm movement path, and diagnostic accuracy of the CASA system.

Software output measures: Software can be divided into two group, proprietary software and open source software. Commercialized CASA systems usually use proprietary software [11], while open source software like Wilson-Leedy and Ingermann [12] is available. Software mainly includes the functions of detection and tracking of sperms and the calculation of sperm movement parameters. What's more, it also provides the results as diagnostic criteria for sperm detection.

2 BASIC THRESHOLDING-BASED METHODS

Threshold segmentation is the most commonly used method among existing sperm detection and localization methods. It converts grayscale images into binary images based on the selected threshold [13]. Threshold segmentation methods include Otsu threshold, adaptive Otsu threshold, iterative threshold, global threshold, local threshold and multi-threshold method. As shown in Figure 1, in this work, the gradient and threshold of the image are first calculated to obtain a binary gradient mask containing segmented cells. Then the threshold is calculated with the Sobel operator. Next, the linear structure element is used to dilate the image to eliminate the linear gap. Finally, the objects on the edge are removed, and the diamond structure is used to erode the image twice to get the segmented object [9].

In [14], the effect of threshold on the calculation of semen samples and kinematic parameters was studied by testing the slight change of threshold (650 gray levels for a total of 2000 gray levels).

In [15], firstly, use threshold operation to separates the pixels represent sperms from other background pixels to detect the corresponding region of a single sperm. However, due to the existence of noise or fragments in the image, the threshold image may have holes and/or jagged boundaries. Then use morphological methods to remove artifacts, fill holes and do some other operations to smooth the boundary of the region, which can help reflect the actual size and shape of sperms. Finally, the regions that differs too much from sperm head in size are removed from the analysis results. This process may fail due to a lack of optical clarity or

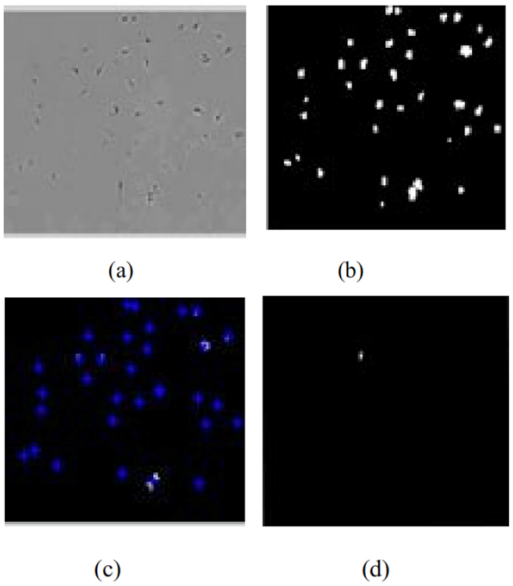


Figure 1: (a) Median filtered image, (b) Segmented image, (c) Centroid of each object, and (d) Spermatozoa Identification. This figure corresponds to Figure 4 in the original paper [9].

boundary-sized areas, and such errors can be handled through user intervention.

In [16], for a particular sperm, the outline image of the sperm is obtained by subtracting two consecutive frames. Then the binary contour image is obtained by applying the threshold to suppress the background noise. The two consecutive frames are subtracted to get the outline of the sperm, which is used for target detection.

In [17], a thresholding-based segmentation method is used to process sperm microscopic video images. Whether the object is the head of sperm is judged through the size of the object and the threshold gray level. The centroid or center of gravity of each unit is calculated according to the coordinates of all the pixels that make up the head.

In [18], our research team adopted the automatic threshold segmentation. The threshold of the image is defined as T, and when the pixel value p is lower than the threshold T, make pendant 0 (black), otherwise make pendant 1 (white). Finally, the result of image segmentation is obtained.

3 CLASSICAL OTSU THRESHOLDING-BASED METHODS

In [19], first, the semen images are divided into foreground images and background images through simple thresholding. The selection of the threshold is based on the Otsu method, which chooses the threshold to minimize the intra-class variance of the black and white pixels. This method works well on images that have a bimodal histogram that sperm images do not have because of the large semen background area compared to the area of cells and the gradually (as opposed to sharply) varying intensity of the cells with the background. Therefore, the binary image does not have enough accuracy. The Otsu threshold method is based on a local

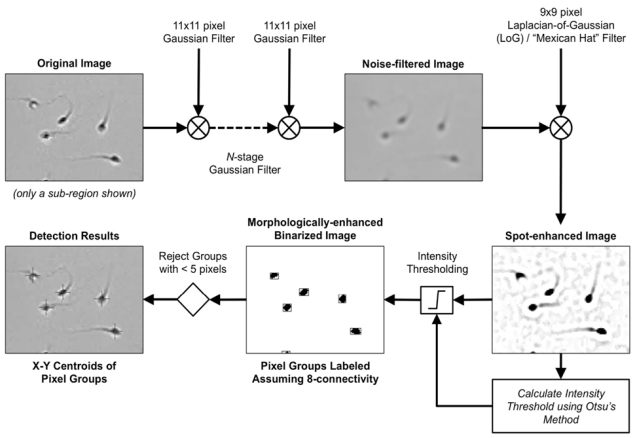


Figure 2: llustration of the sperm segmentation and localization algorithm. This figure corresponds to Figure 1 (b) in the original paper [21].

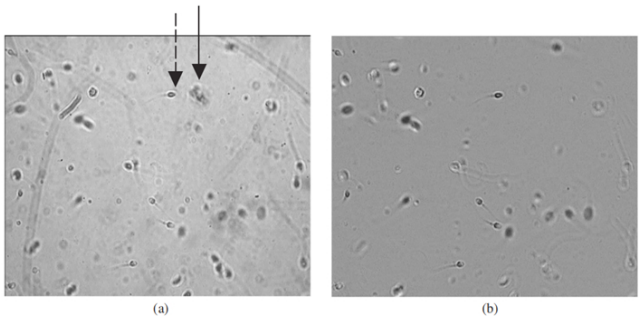


Figure 3: Applying the enhancement algorithm to an image: Raw (a) and enhanced (b) images. This figure corresponds to Figure 1 in the original paper [25].

image histogram instead of the whole histogram. To implement the Otsu threshold, first, select an area recognized in the binary image, then apply the Otsu method on a small square, for example, an 8×8-pixel box is used here, and then detect the sperm according to this square. Finally, the new threshold is obtained.

In [20], the region of interest can be automatically selected and, by using the Otsu criterion, a binary image of the object is obtained. This image is used to find the same object in each phase diagram image for target detection.

In [21], the algorithm first convolves the original image successively with an 11×11 Gaussian filter (commensurate with the size of a sperm head) to reduce image noise and soften halo edge pixels. Spot-enhancement is achieved by using a 9×9 Laplacian-of-Gaussian (LoG) ("Mexican-hat") filter to increase the contrast between sperm heads and their surrounding halo. Next, the spot-enhanced image is binarized by using an intensity threshold calculated with the Otsu method [22] and multiplied by a user-specified weighting factor. After this, to reduce spurious detection, the binarized images are morphologically eroded and dilated with a 5×5 and 3×3 diamond structuring element, respectively. Then, groups of pixels should be labeled as eight-connectivity, and any group having less than 5 pixels is considered as a non-sperm particle and discarded. The centroid of each pixel group is calculated and regarded as a sperm position measurement. Finally, they detect sperm in this way. A new comprehensive method is adopted to detect and locate sperm. With this method, sperm cell detection accuracy is approximately 95% and the false detection rate is less than 1% (estimates based on comparison with manual detection of sperm in five random frames). The working flow chart of sperm detection is shown in Figure 2

4 ADAPTIVE OTSU THRESHOLD-BASED METHODS

In [23], a 40×40 sperm head region of interest (SHROI) image is obtained from the current frame. First, the center of the SHROI image is initialized at the mouse clicked position. Then, the SHROI image is binarized by applying the Otsu adaptive thresholding algorithm [22]. Thirdly, a close morphological operation is performed to remove noise and small particles present in the SHROI image. Finally, the end product is a binary SHROI image, where the pixel values are ones for objects and zero for others. Furthermore, the contour of the sperm heads in the SHROI image is computed, and the centroid of the sperm heads are found by calculating the moment of the contour.

In [24], to get the detection target, the system obtains a 40×40 sperm head region of interest (SHROI) from the current frame i. The center of the SHROI image is initialized at the mouse clicked position. The SHROI image is binarized by applying the Otsu adaptive thresholding algorithm, where the contour of the sperm head in the SHROI image is computed.

5 SEMI-AUTOMATIC METHODS

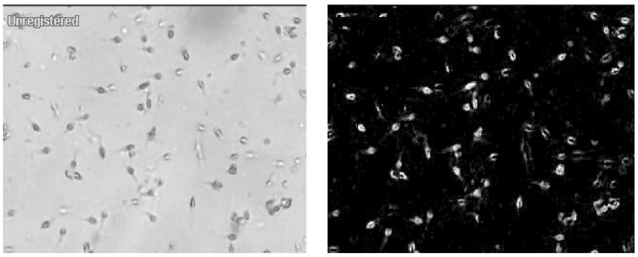
In [25], after enhancing the image quality, the lab technician selects the specific sperm manually. To do so, technical personnel clicks, using the computer cursor, on the desired point at the first frame of the video previously saved on the computer. This point is, then, used by the computer as the initial point for a template matching algorithm. The detection algorithm should determine the sperm's location in the next frames. The comparison of raw image and processed image is shown in Figure 3

In [26], sperm head area is tracked manually in the time-sequence images by using the freely available image processing software ImageJ [27]. Centroids of the sperm heads are used to calculate the sperm position in the tow plane.

6 FILTERING METHODS

In [28], first, by using proper structure elements, the image sequences are filtered based on Top-hat operation to separate sperm cells from other debris. Then, the rest of the noisy objects which are smaller than sperm heads are reduced by the open operation. An adaptive temporal median filter is employed to separate the background from the foreground. The detection results are shown in Figure 4

In [29], a Gaussian Mixture Model (GMM) is enhanced by Hole Filling Algorithm (GMMHF) as their previous researches showed. GMM is formulated as the probability of every pixel is background



(a) (b)

Figure 4: Shows preprocessing. (a) Origin. (b) Morphological filtering and background removal. This figure corresponds to Figure 1 in the original paper [28].

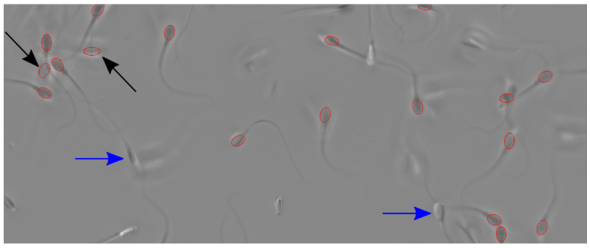


Figure 5: Part of the head detection result. The contours of the detected heads are depicted in red. The blue (horizontal) arrows indicate the missed detections, and the black (diagonal) arrows point to the false alarms. This figure corresponds to Figure 3 in the original paper [31].

or foreground, with its probability density function. The result binaries of foreground and background are obtained by a large number of probability calculations. In this work, the researchers compare other methods with GMMHF, and conclude that, although it is not the most accurate detection algorithm, it requires a relatively small amount of computation.

7 SHAPE FITTING METHODS

In [30], a target object is approximated by a rectangle region. The state of the target object at the current frame can then be described by parameters of the rectangle, where two parameters represent the image coordinates of the rectangle center, and another one denotes the angle between the major axis of the object and the image coordinate system.

In [31], the researchers use modeling to detect and localize sperm heads. Their modeling uses an ellipse to represent a head. Hence, a head is represented by five parameters, denoted as (x; y; a; b; ∅), where (x; y) are coordinates of the center point, a and b are the lengths of the major and minor axes, respectively, and ∅ is the angle between the major axis and the horizontal direction. Using such a representation, the goal of the head detection becomes to detect an unknown number of ellipse-shaped objects. To achieve this goal, an improved multiple birth and cut (MBC) algorithm based on marked point processes [32] is used. A work performs the head detection every 100 frames to make sure that if the sperms are missed with the detection algorithm on the previous frames, they still can be detected on later frames. Figure 5 shows some detection results.

8 UNSUPERVISED LEARNING-BASED METHODS

In [10], they use an approach called Spatio-Temporal Segmentation to detect sperm. Segmentation of video sequences by modeling the video data as multidimensional space-time data is applied in this work. It integrates k-means, GMM, mean shift and other segmentation detection and background separation algorithms.

In [33], the use of optical capture method for sperm detection is applied, where computer methods are used to assist manual work.

9 OPTIMUM BINARIZATION-BASED METHODS

In [34], different algorithms are integrated for a sperm segmentation task, including grayscale conversion, background identification, background subtraction, binarization, and binary morphology approaches. Firstly, the background is subtracted from every frame in the video. This removes the microchannel walls and artifacts that could be confusing for object detection. After this, maximum entropy is identified as the optimum binarization technique to detect sperms. An example of this method is shown in Figure 6. It mentions that other algorithms that give good results include using Renyi's entropy and Sauvola local thresholding.

10 ANALYSIS

Clinically, there are many impurities in semen samples, some of which are similar in size and shape to sperm. None of the sperm detection methods mentioned in this paper can make a good distinction between sperm and impurities and it can be a new research direction in this field. In recent years, with the increasing application and continuous development of deep learning, in the literature we consult, deep learning methods are hardly used in this field. Therefore, we should try to introduce deep learning in target detection and explore their potential to achieve better performance in this field.

11 CONCLUSION

According to the relevant literatures in the past 30 years, it can be seen that thresholding-based sperm detection methods are widely used, including Global thresholding, Otsu, Adaptive thresholding, and Multilevel thresholding. The main reason is that the threshold-based sperm detection methods are simple and easy to apply, and of high accuracy. As for detection methods like Semi-automatic Methods, Unsupervised Learning based Methods, Shape Fitting Methods and self-developed detection algorithms, they are hardly used. These alternatives show more possibility in detection and make threshold-based algorithms better deal with different detection challenges on sperm microscopic video.

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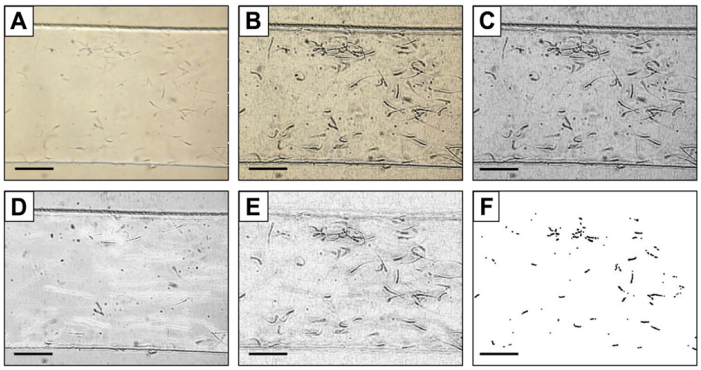

Figure 6: Object detection pipeline: (a) original image; (b) result of local contrast enhancement (contrast-limited adaptive histogram equalization); (c) grayscale conversion; (d) background generation: 90 frames were merged to create this background; (e) background subtraction; (f) binarization using maximum entropy followed by opening. Scale bars: 50 μm. This figure corresponds to Figure 2 in the original paper [26].

REFERENCES

[1] Agarwal, A., Mulgund, A., and Hamada, A. 2015. A unique view on male infertility around the globe. *J. Reproductive Biology and Endocrinology.* 13, 1 (Apr, 2015), 37. DOI=http://doi.org/10.1186/s12958-015-0032-1.

[2] Leung, C., Lu, Z., and Esfandiari, N. 2011. Automated sperm immobilization for intracytoplasmic sperm injection. *J. IEEE Trans Biomed Eng.* 58, 4 (Apr. 2011), 935-942. DOI=https://doi.org/10.1109/TBME.2010.2098875.

[3] W.H. Organisation. 1999. WHO laboratory manual for the examination of human semen and sperm-cervical mucus interaction. *J. Journal of Andrology.* 17, 4 (1999), 442-442. DOI=https://doi.org/10.1002/j.1939-4640.1996.tb01811.x.

[4] Menkveld, R., Holleboom, C. A., and Rhemrev, J. P. 2010. Measurement and significance of sperm morphology. *J. Asian Journal of Andrology.* 12, 1 (2010), 47. DOI=http://doi.org/10.1038/aja.2010.67.

[5] Tomlinson, M., Lewis, S., and Morroll, D. 2013. Sperm quality and its relationship to natural and assisted conception: British Fertility Society guidelines for practice. *J. Hum Fertil (Camb).* 16, 3 (Sep, 2013), 175-193. DOI=http://doi.org/10.3109/14647273.2013.807522.

[6] Holt, W., Watson, P., and Curry, M. 1994. Reproducibility of computer-aided semen analysis: comparison of five different systems used in a practical workshop. *J. Fertility and Sterility.* 62, 6 (1994), 1277. DOI=http://doi.org/10.1006/excr.1994.1358.

[7] Verstegen, J., Iguerouada, M., and Onclin, K. 2002. Computer assisted semen analyzers in andrology research and veterinary practice. *J. Theriogenology.* 57, 1 (2002), 149-179. DOI=http://doi.org/10.1016/S0093-691X(01)00664-1.

[8] Larsen, L. 2000. Computer-assisted semen analysis parameters as predictors for fertility of men from the general population. *J. Human Reproduction.* 15, 7 (2000), 1562-1567. DOI=http://doi.org/10.1093/humrep/15.7.1562.

[9] Abbiramy, V, S., Shanthi, V., and Allidurai, C. 2010. IEEE 2010 International Conference on Signal and Image Processing (ICSIP) - Chennai, India (2010.12.15-2010.12.17). 2010 International Conference on Signal and Image Processing - Spermatozoa detection, counting and tracking in video streams to detect asthenozoospermia. (Dec. 2010), 265-270.

[10] Michael, B., Hayit, G., and Daniel, C. 2007. Segmentation and tracking of human sperm cells using spatio- temporal representation and clustering. *J. Proceedings of SPIE - The International Society for Optical Engineering.* 6512 (2007), 65122M-65122M-12. DOI=http://doi.org/10.1117/12.708887.

[11] Amann, R. P., Waberski, D. 2014. Computer-assisted sperm analysis (CASA): capabilities and potential developments. *J. Theriogenology.* 81, 1 (2014), 5-17.e3. DOI=http://doi.org/10.1016/j.theriogenology.2013.09.004.

[12] Wilson-Leedy, J. G., Ingermann, R. L. 2007. Development of a novel CASA system based on open source software for characterization of zebrafish sperm motility parameters. *J. Theriogenology.* 67, 3 (Feb, 2007), 661-72. DOI=http://doi.org/10.1016/j.theriogenology.2006.10.003.

[13] Bhargavi, K., Jyothi, S. 2012. A Survey on Threshold Based Segmentation Technique in Image Processing. *J. International Journal of Innovative.* 3, 12 (Nov, 2014), 234-239.

[14] Kraemer, M., Fillion, C., and Martin-Pont, B. 1998. Factors influencing human sperm kinematic measurements by the Celltrak computer-assisted sperm analysis system. *J. Human Reproduction.* 13, 3 (1998), 611. DOI=http://doi.org/10.1093/humrep/13.3.611.

[15] Tomlinson, M. J., Pooley, K., and Simpson, T. 2010. Validation of a novel computer-assisted sperm analysis (CASA) system using multitarget-tracking algorithms. *J. Fertility & Sterility.* 93, 6 (2010), 1911-1920. DOI=http://doi.org/10.1016/j.fertnstert.2008.12.064.

[16] Liu, J., Leung, C., and Lu, Z. 2013. Quantitative analysis of locomotive behavior of human sperm head and tail. *J. IEEE Transactions on Biomedical Engineering.* 60, 2 (Feb, 2013). DOI=http://doi.org/10.1109/TBME.2012.2227319.

[17] Mack, S. O., Wolf, D. P., and Tash, J. S. 1988. Quantitation of specific parameters of motility in large numbers of human sperm by digital image processing. *J. Biol Reprod.* 38, 2 (Mar, 1988), 2. DOI=http://doi.org/10.1095/biolreprod38.2.270.

[18] Li, X., Li, C., and Kulwa, F. 2020. Foldover Features for Dynamic Object Behaviour Description in Microscopic Videos. *J. IEEE Access.* PP, 99(2020), 1-1. DOI=http://doi.org/10.1109/ACCESS.2020.3003993.

[19] Nafisi, V.R., Moradi, M.H., and Nasr-Esfahani, M. H. 2004. Sperm Identification Using Elliptic Model and Tail Detection. *J. World Academy of Science, Engineering and Technology 6.* (Nov, 2004), 205.

[20] Di, C. G., El, M. A., and Ferraro, P. 2014. 4D tracking of clinical seminal samples for quantitative characterization of motility parameters. *J. Biomed Opt Express.* 5, 3 (Mar, 2014), 690-700. DOI=http://doi.org/10.1364/BOE.5.000690.

[21] Urbano, L. F., Masson, P., and Vermilyea, M. 2017. Automatic Tracking and Motility Analysis of Human Sperm in Time-Lapse Images. *J. IEEE Trans Med Imaging.* 36, 3(Mar, 2017), 792-801. DOI=http://doi.org/10.1109/TMI.2016.2630720.

[22] Otsu, N. 1979. Threshold Selection Method from Gray-Level Histograms, IEEE Transactions on Systems Man and Cybernetics. *J. IEEE Trans.syst.man Cybern.* 9, 1 (1979), 62-66. DOI=http://doi.org/10.1109/TSMC.1979.4310076.

[23] Leung, C., Lu, Z., and Esfandiari, N. 2010. Detection and tracking of low contrast human sperm tail. *2010 IEEE International Conference on Automation Science and Engineering.* (2010), 263-268.

[24] Lu, Z., Zhang, X., and Leung, C. 2011. Robotic ICSI (intracytoplasmic sperm injection). *J. IEEE Trans Biomed Eng.* 58, 7 (Jul, 2011), 2102-2108. DOI=http://doi.org/10.1109/tbme.2011.2146781.

[25] Nafisi, V. R., Moradi, M. H., and Nasr-Esfahani, M. H. 2005. A template matching algorithm for sperm tracking and classification. *J. Physiological Measurement.* 26, 5 (Oct, 2005), 639. DOI=http://doi.org/10.1088/0967-3334/26/5/006.

[26] Nosrati, R., Driouchi, A., and Yip, C. M. 2015. Two-dimensional slither swimming of sperm within a micrometre of a surface. *J. Nature Communications.* 6 (Nov, 2015), 8703. DOI=http://doi.org/10.1038/ncomms9703.

[27] ImageJ. Website of imagej. Available at: https://imagej.nih.gov/ij/ (2020).

[28] Ravanfar, M. R., Moradi, M. H. 2011. Low contrast sperm detection and tracking by Watershed algorithm and Particle filter. *2011 18th Iranian Conference of Biomedical Engineering (ICBME).* (2011), 260-263.

[29] Nurhadiyatna, A., Latifah, A. L., and Fryantoni, D. 2015. Comparison and implementation of motion detection methods for sperm detection and tracking. *International Symposium on Micro-nanomechatronics and Human Science (IEEE).* (Jan, 2015), 1-5.

[30] Zhou, X., Lu, Y. 2010. Efficient Mean Shift Particle Filter for Sperm Cells Tracking. *International Conference on Computational Intelligence and Security(IEEE).* (2010), 335-339.

[31] Yang, H. F., Descombes, X., and Prigent, S. 2014. Head Tracking and Flagellum Tracing for Sperm Motility Analysis. *2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI)* (2014), 310-313.

[32] Soubies, E., Weiss, P., Descombes, X. 2015. Graph Cut Based Segmentation of Predefined Shapes: Applications to Biological Imaging. *Pattern Recognition Applications and Methods. Springer International Publishing.* 2015.

[33] Shi, L. Z., Nascimento, J., and Chandsawangbhuwana, C. 2006. Real-time automated tracking and trapping system (RATTS). *J. Microscopy Research and Technique.* 69, 11 (Nov, 2006), 894-902. DOI=http://doi.org/10.1002/jemt.20359.

[34] Elsayed, M., El-Sherry, T. M., and Abdelgawad, M. 2015. Development of computer-assisted sperm analysis plugin for analyzing sperm motion in microfluidic environments using Image-J. *J. Theriogenology.* 84, 8 (Nov, 2015), 1367. DOI=http://doi.org/10.1016/j.theriogenology.2015.07.021