Human Sperm Tracking using Particle Swarm Optimization combined with Smoothing Stochastic Sampling on Low Frame Rate Video

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***Abstract*—In this paper, we present a technique for visual tracking in the field of Human Sperm motion. Application of sperm cell tracking is mainly important in Intracytoplasmic Sperm Injection (ICSI), a medical procedure that has enabled the In Vitro Fertilization (IVF) of a single sperm which is injected directly into an egg. In this paper, we consider the problem of tracking single object in video sequences of human sperms and a newly developed Smoothing Stochastic Approximate Monte Carlo (SSAMC) based tracker enhanced by Particle Swarm Optimization (PSO). The problem for this research is that the motility or movement of Human Sperm is fast and unpredictable. In addition, each and every sperms have closely similar size and shape. To solve this problem, we used PSO for searching algorithm (finding the best target) in a Search Window, it can reduce the search space in every each consecutive frame. The measurement results of the proposed method are then compared with the manual measurements done by experts. The experiment results were conducted on both open video data and our own video data. Experiment results showed that the proposed method can handle our specific problem in human sperm cell tracking, and give us a better result as compared to our previous tracker, which used geometric transition dynamic model and without any enhancement by PSO.**

Keywords: PSO, Human Sperm Cell Tracking, SSAMC, Search Window

I. Introduction

In-Vitro Fertilization (IVF) method is one of the most popular techniques in assisting couples with infertility problems. This fertilization process can be conducted by putting both of the egg and sperm cells inside a cup or glass-like containers or by injecting the sperm to the egg cell by a process called Intracytoplasmic Sperm Injection (ICSI). The fact is success rate of IVF relatively low, around 30-40 %. These failures are determined by many factors, including the quality of the sperm used during the ICSI process. Furthermore, characteristic of sperm movement or sperm motility is one of the most important aspect to determine the quality of the sperm. Human sperm quality assessment was provided by World Health Organization (WHO) in 2010 [1]. Motility, vitality and morphology of sperm cell are assessed as sperm quality factor. According to those criteria, WHO categorize sperm motility into 4 categories that can be seen in Table I.

TABLE I
Human Sperm Motility Classication By World Health Organization (WHO) [1]

No.	Grades	Name	Movements μm/s
1	A	Rapid progressive motility	25
2	B	Slow progressive motility	5 <speed <25
3	C	non-progressive motility	<5
4	D	Immotility	No Movements

Since we know that sperm quality assessment plays an essential role in human fertility and animal breeding, and manual analysis by expert is very time-consuming, and in other hand if we are looking for an accurate analysis to assess the sperm quality, we also need a means of statistical analysis that may not be achieved by visual assessment from human or expert, so the automation of analyzing sperm motility is necessary.

Research in field of human sperm tracking has been approached by some researchers. Human sperm motility analysis from video data is one of the active research area nowadays. The common problem that existed in this research are sperm cell detection and tracking. Previous research by Xiuzhuang Zhou et al [2] proposed an integration of Particle filter and mean shift based mode seeking to effieciently capture the uncertain motions of the sperm cells. Particle filter facilitates the tracking by exploring in state space of the target distribution to avoid getting trapped in local optimal mode. Mean-shift based local optimization aims at fast location of the local optimal mode and facilitates the estimate of local optimal orientation. Ravanfar et al [3] proposed sperm tracking method based on Watershed segmentation and Particle filter estimation which focuses on the sperm collision problem. The tracker estimates motion direction of sperms regardless of sperm head orientation and tries to employ morphological characteristics along motion features in order to weight particles.

Currently, the Particle Swarm Optimization (PSO) and its variants are most extensively used in video-based tracking problem. Several research that employed PSO as a method to track object had been done by [4], [5], [6]. The reason why they used PSO because it offers several advantages such as the ability to solve highly nonlinear problem, robust and reliable performance, global and local search capability [7].

The aim of this research is to enhance our previous tracker [8]. In our previous tracker, we used geometric transition dynamic model and develop tracking algorithm based on bootstrap particle filter. In our previous method, we failed to track sperm cell because of the sperm motility characteristics. In addition, the sperm target is among the many sperms which have similar size and shape.

In this paper we consider the problem of tracking single object in video sequences of human sperms and a newly developed Particle Swarm Optimization combined with Smoothing Stochastic Approximate Monte Carlo for the tracker. The problem for this research is the motility or movement of Human Sperm is fast and unpredictable. Furthermore, our video sequences of human sperms were taken by low frame rate cameras which only has 20 fps for efficiency storage for human sperm data record, so that the sperm-motion more abrupt. The other challenge in this research is the fact that every single sperm cell has a similar shape and size, so with applying limitation for search space in each frame can help us to solve this challenge like Ravanfar et al [9].

In section 2, the background method that used in this proposed method will be described. Basic concept of Particle Swarm and Smoothing Stochastic Approximate Monte Carlo will be provided. Design of proposed method is described in Section 3. Experiments result is presented in Section 4, and the performance of the proposed method is evaluated for two real scenarios, one with open data (good frame rate) and the other one with our own data (low frame rate). The conclusion and further discussion as open problem of this paper are briey discussed in the last section of the manuscript.

II. BACKGROUND

After we know the requirement for automated sperm immobilization is robust tracking algorithms that are capable of handling abrupt motions, then the main objective of this research is to make a tracker that can handle abrupt motions robustly. We employed Particle Swarm Optimization and Smoothing Stochastic Approximate Monte Carlo to find the target object and combined with windowing technique to localize the search space. The brief description about background methods are described as follows:

A. Basic Concept of PSO

Particle Swarm Optimization is a method to find the optimum solution which is popularly used, introduced by R.C. Eberhart dan J. Kennedy on 1995 [10]. This method is a modification of swarm intelligence method which itself is an optimization method. This method is inspired from natural phenomenon, modeling the communication done between individuals in a population on achieving optimum value. Until now, there are several variations of Swarm Intelligence method such as Genetic Algorithm, Artificial Bee Colony Algorithm, Firefly Algorithm, Cuckoo Search and many more [11]

PSO is an algorithm modeled after bird, fish, and bee behavior in search of food simulation within a population. In PSO, each individuals is represented by vector (X_{in}) which shows individual's position. Each individual is also represented by vector that shows movement direction called velocity vector (V_{in}). In each iteration, the PSO moves the particles to optimum solution appropriate by the information owned by velocity vector which updated in each iteration The formulation of that behavior can be seen at equation 1. As for the formulation to update individuals position can be done by formula in equation 2 [10].

$$V(t+1) = V(t) + c_1 \cdot rand() \cdot (P_{best} - P_t) + c_2 \cdot rand() \cdot (G_{best} - P_t) \quad (1)$$

$$X(t+1) = X(t) + V(t+1) \quad (2)$$

where :

- $V_i^{(n+1)}$ denotes the velocity vector of the ith individual during $(n+1)$ iteration,
- c_1 and c_2 denotes individual and social component constant respectively,
- p_i^n denotes local best value position of individual i during nth iteration,
- p_g^n denotes global best value position of individual i during nth iteration,
- x_i^n position of individual i during nth iteration,
- x_i^n+1 position of individual i during $(n+1)$ iteration,
- and $rand()$ denotes function that maps to a random value between (0-1).

A particular behaviour in PSO is that it always updates the local best position and global best position and then the velocity vector until a certain condition is achieved. That conditions are:

1) Searching time is exceeding the limit allowed.
2) Optimum solution within threshold has been found.
3) There is no improvement within a limit of iteration.

B. Smoothing Stochastic Approximate Monte Carlo

1) Bayesian Formulation: The value of a hidden state x_t from a set of observation $z_{1:t} = \{z_1 \ldots z_t\}$ and a discrete time index t can be estimated by visual tracking of moving objects which is modelled as a Markov process. By employing Bayes theorem, object tracking problems can be described [12] as follows:

Prediction :

$$p(x_t|z_{1:t-1}) = \int p(x_t|x_{t-1})\, p(x_{t-1}|z_{1:t-1})\, dx_{t-1} \quad (3)$$

Update:

$$p(x_t|z_{1:t}) = \frac{p(z_t|x_t)\, p(x_t|z_{1:t-1})}{p(z_t|z_{1:t-1})} \quad (4)$$

The resultant probability distribution $p(x_t|z_{1:t})$ should satisfy the axioms of probability and sums up to 1. The aforementioned characteristic is ensured by the denominator $p(x_t|z_{1:t-1})$ which represents normalization factor. Variation of object tracking problems differ in forms of the observation model $p(z_t|x_t)$ and the transition model $p(x_t|x_{t-1})$, and propose different methods in resolving this recursion based on their problem requirements. The core of solving object tracking problems is solving the recursive Bayesian solution. Finally, optimal state of state at the time t can be estimated by maximum a posterior (MAP):

$$\hat{X}_t = arg\ max\ p\left(x_t|z_{1:t}\right) \tag{5}$$

2) Metropolis-Hastings Algorithm: The first sampling algorithm for this implementation of the numerical recursive Bayesian solution is metropolis algorithm [13]. This algorithm is then generalized by Hasting in 1970 [14] to allow the empowerment of asymmetric proposal distribution. The algorithm is performed in two consecutive stages, which called as proposal-decision steps:

1) **Proposal.** Draw candidate state x_t' from a proposal function $Q(x_t'|x_t)$ given the current state x_t . The common design of proposal function is based upon the transition model $p(x_t|x_{t-1})$ as random unbiased perturbation of the current state.
2) **Decision.** Compute the acceptance probability α, to determine whether the candidate is accepted or rejected. The parameter α is the ratio of likelihood between the candidate and the current sample. Thereupon, multiplied by the correcting factor for compensating the asymmetric proposal:

$$\alpha(x_t'|x_t) = min\left\{1, \frac{p(x_t'|z_{1:t})\ Q(x_t|x_t')}{p(x_t|z_{1:t})\ Q(x_t'|x_t)}\right\} \tag{6}$$

Localness, the new state being generated in a neighborhood of the current state is a fundamental feature of Metropolis-Hastings. Complex task would be split into a series of manageable pieces by employing the aforementioned feature. On the other hand, there are drawbacks of this feature, i.e. local trap problem when the posterior distribution has multiple separated local minima. Consequently, the target of interest cannot be estimated accurately due to the failure of the simulation process to sample from the relevant parts.

To cope with this type of difficulty, there are two main strategies. Firstly, the utilization of a global updating scheme, for instance: simulated annealing [15] which introduces new temperature variable to purvey a global proposal. Secondly, to sample from an assembly on which each configuration covers certain sample space. Therefore, the local trap problem does not exist anymore. The Stochastic Approximate Monte Carlo (SAMC) [16] utilizes the second strategy. And its variant, Smoothing Stochastic Approximate Monte Carlo (SSAMC) is an improvement of SAMC, by augmenting a smoothing step for increasing the efficiency. In subsequent section, we discuss SSAMC sampling method and implement it in visual tracking problem.

3) Tracking by using Stochastic Sampling: The same as our previous method [17], now we are using search window to make our tracker focus in a specific neighborhood around the sperm target and then avoid unnecessary observations. The state of the target $x_t = (x_t^p, x_t^s)$ at time t consists of position and scale of the object. And the state space of position S is defined by a set of all possible state position in image, called as image space. Next we define $S^W \subseteq S$ as search window that contain search space in every frame. Search Window S^W is then divided into m disjoint sub-regions, according the energy function $E(x)$:

$$S^W = \bigcup_{i=1}^{m} E_i,\ E_i \cap E_j = \oslash\ for\ i \neq j \tag{7}$$

Next, posterior distribution: $E(x) = p(x_t|z_{1:t})$ as the energy function. Based on our previous [17], rectangular with 30x30 pixel will be used as the Search Window. Next step is designing an effective sampler to simulate random walks in the sub-regions (in this case Search Window divided into 9 subregions) so that the abrupt motions can be captured,called as weighted trial function [16]:

$$p_\omega = \sum_{i=1}^{m} \lambda_t^i \frac{p(x_t|z_t)}{\omega_i} I(x_t \in E_i) \tag{8}$$

Where $I(.)$ is indicator function, λ_t^i is the confidence of the i-th sub-region at time t, which controls the sampling frequency of this sub-region, and ω_i is density of states (DOS) in the i-th sub-region:

$$\omega_i = \int_{E_i} p(x_t|z_{1:t}) dx_t \tag{9}$$

From equation above, λ_t^i will be used to control the similarity between the posterior distribution $p(x_t|z_t)$ and the trial distribution $p_\omega(x_t)$. We can integrate any priors into trial distribution by adjusting this parameter. Furthermore the trial distribution plays the key role for defining the acceptance probability in decision step.To increase efficiency, the estimation of parameter ω_i will be updated each iteration by using smoothing process, which incorporated in the sampling algorithm.

4) Proposal Step: In this step, we choose the proposal function based on the motion of target, can impact to the tracking performance remarkably. In this proposal function, we introduce two basic moves, namely global random walk and local random walks. The global random walk is performed to anticipate the large motion uncertainty. The other one, the local random walk is designed to explore around the current state since human sperm is generally moves smoothly. Thus the proposal distribution is formulated as:

$$Q(x_t'|x_t) = \beta N(x_t'|x_t, \sum) + (1-\beta) Q_g(x_t'|x_t) \tag{10}$$

Where the parameter $\beta \in [0,1]$ balances the proposal between the global random walk and the local random walk.

And $N(x_t'|x_t,\Sigma)$ is a normal distribution with mean $\mu = x$ and and variance $\Sigma = (\delta_x^2, \delta_y^2, \delta_s^2)$. Next, we have to adjust the corresponding variances of state parameters and assume it does not change over time. The normal distribution represents the local random walk. While $Q_g(x_t'|x_t)$ and $x' \in E_i$ which represents the global random walk, and it is defined as follow:

$$Q_g(x_t'|x_t) = \begin{cases} \theta & if \quad \lambda_t^i > 0 \\ 1-\theta & otherwise \end{cases} \tag{11}$$

5) Acceptance Step: Suppose that a candidate sample x_t' has been generated using the above proposal function, thus the acceptance probability α is formulated as:

$$\begin{aligned} \alpha(x_t') &= min\left(1, \ \frac{p_\omega(x_t') \ Q(x_t|x_t')}{p_\omega(x_t) \ Q(x_t'|x_t)}\right) \\ &= min\left(1, \ \frac{p(x_t'|Z_{1:t}) \ \frac{\lambda_t'^i}{\omega_i'} \ Q(x_t|x_t')}{p(x_t|z_{1:t}) \ \frac{\lambda_t^i}{\omega_i} \ Q(x_t'|x_t)}\right) \end{aligned}$$

First, the density of each sub-region is not set as 0, but set according to its confidence as: $\omega_i = exp(-1000 \times \lambda_t^i)$. Our acceptance probability has the main advantage because during tracking, the confidence value λ_t^i always drives our sample to accept the candidate in promising regions. This enhances the sampling efficiency by reducing rejection rate.

6) Smoothing Step: In our proposed method, SAMC algorithm depends on self-adjusting mechanism, which enables the sampler to explore the entire image space. But the SAMC ignores the difference between the neighboring and non-neighboring regions, and then it does not reach the maximal efficiency. we can improve sampler efficiency by distributing the information contained in each sampling to its neighboring through updating ω_i^k , the density parameter in the i-th sub-region at each iteration k. This is the main idea of smoothing-SAMC or SSAMC [16] and implemented by adding a smoothing step.

Like our previous method, in our proposal step, multiple sample are generated at each iteration and then we employ a smoothed estimator f_i^k when updating the density parameter ω_i^k. Parameter f_i^k is the probability that a sample can be drawn from the i-th sub-region with energy function Ei at iteration k. Let $X_t^1, X_t^2, ...X_t^n$, denote as set of n samples accepted in decision step. If accumulation of accepted sample in certain region at iteration k is:

$$r_i^k = \sum_{j=1}^{n} I(X_t^j \ \in \ E_i) \tag{12}$$

Then, by using Nadarya kernel estimation [16], we can calculate the smoothed estimator when there is d sub-regions as:

$$f_i^k = \frac{\sum_{j=1}^{d} W(M(i-j)) \ r_j^k/n}{\sum_{j=1}^{d} W(M(i-j))} \tag{13}$$

Where $M(i-j)$ measure the eulidean distance between centers of sub-regions Ei and Ej. $W(.)$ is double-truncated

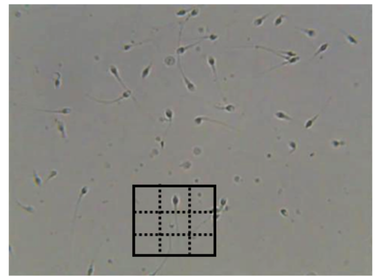

Fig. 2. Illustration of Searching Window

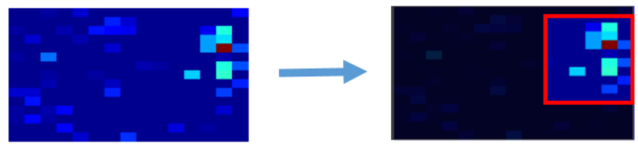

Fig. 3. Effect of Searching Window

Gaussian kernel function to control the smoothing scope. After calculating the smoothed estimation f_i^k, the next step is updating the density parameter with equation below:

$$\begin{aligned} \omega_i^{k+1} &= \omega_i^k + exp(\gamma_k(f_i^k - \pi_i)), \\ i = 1,2,....,d, \quad \gamma_k &= \frac{k_0}{max(k_0,k)} \end{aligned} \tag{14}$$

In the equation above, parameter λ_k is a gain factor that used to control the updating speed of the density parameter. k_0 is a predefined constant and π_i is the desired sampling frequency of each sub-region. Parameter π_i can be thought as our prior knowledge about sample space and if we dont have any knowledge, it simply can be set as uniform distribution.

III. METHODOLOGY

The main pipeline of the proposed method can be seen in fig. 1. The process starts with preprocessing, and then followed by windowing technique to localize the search space. After previous stage, the next step is tracking object by SSAMC and finding the best position of the target (human sperm cell) by using PSO.

A. Windowing Technique to Reduce Search Space

After we know the fact that the sperm target has similar size and shape among many others sperms, and unpredictable sperm movement make a possibility of occlusion in tracking scenes, we use a windowing technique to reduce the search space. This technique aims to avoid unnecessary observations, and we also only focus in a specific neighborhood around the sperm target. Based on our previous research experiments, we choose $30x30$ pixel for windows size. Illustration of widowing technique can be seen in fig. 2. The search window ensure that the dimension of search space will be reduced.

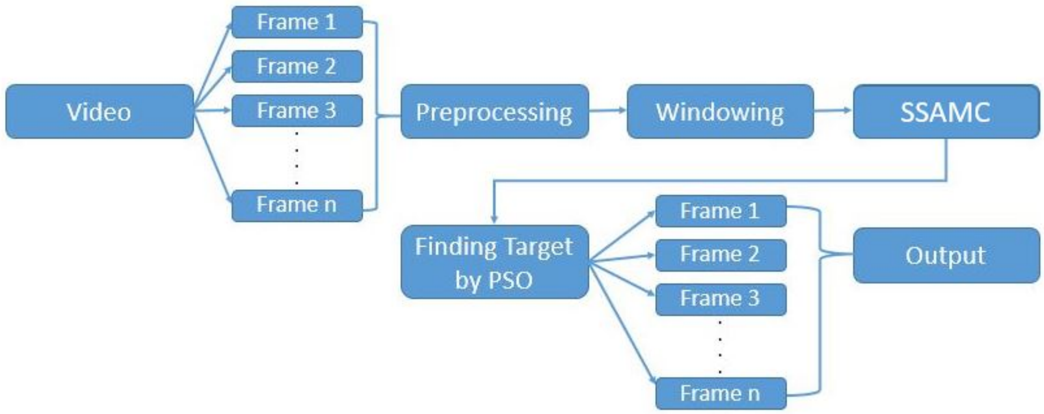

Fig. 1. Main Pipeline of Our Propose Method

B. Finding target by Using PSO

In this section, we introduced the proposed tracking algorithm by using PSO to detect the target object. Our algorithm localizes the tracked object in each image frame using a rectangular window, and the motion of a tracked object between two consecutive frames is approximated by ANNF [18]. We employ ANNF to provide the possibility target position by the confidence of a pixel, the illustration can be seen in fig. 3. In term of detection, we use simple implementation of PSO. We define the particle of PSO as $xt = (x, y, w, h)$ where $\{x, y\}$ denote the location of the particle in the frame, and $\{w, h\}$ denote the high and width of the particle. Moreover, fitness value of each particle is evaluate by the intensity and value from the result of previous stages.

IV. RESULT

In order to evaluate our proposed method, experiments has been done by using video data to track the movement of a human sperm cell. The experiments are implemented on Intel i7 2.40 GHz CPU with 4 Gigabytes RAM. Our experiments are done by using two video data, the first data retrieved from Kokopelli Technology [19], and the second data retrieved from Dr. Cipto Mangunkusumo Hospital Lab.

Evaluation is done by calculating the accuracy of our proposed method, The accuracy formulation is defined as follows:

$$accuracy = \frac{TP + TN}{N} \tag{15}$$

Accuracy is the ratio of the number of data to be recognized correctly by the algorithm against the entire data set. The accuracy of the detection is measured by calculating the hit rate of the result. A cell sperm is said to be detected (hit) if the error of the approximation location for sperm cell value is less than a certain limit, which for this experiment is 10 pixels [20].

The result of our experiment can be seen in table II. In the table we can see our proposed method perform better compared with previous method. In fig. 4 we compare our proposed method with our previous method [17] that successfully track the human cell sperm object. In the result we can see our approach can face the challenging problems (a fast motion, low frame rate, and possibility occlusion). Our proposed method can handle the challenge of this tracking problem because we use several approaches. Firstly, by using PSO and combined with SSAMC, our approach can handle sperm move abruptly problem. Utilization of AANF can increase the confidence of our tracker because the mechanism to find promising regions of the target and make PSO detected target correctly. Secondly, utilizing of Search Window can help us to make sure we only focus on target that we want to track.

TABLE II
COMPARISON RESULT

Method	Acuracy	
	Kokopeli's Video	**Our Own Video**
Previous method [17]	0.89	0.79
Our Proposed Method	**0.91**	**0.85**

V. CONCLUSION

From the experiments that have been performed, it can be concluded that the proposed method can perform human sperm cell tracking on low frame rate video. Our approach successfully enhance our previous tracker [17]. Our approach is combining Particle Swarm based method combined with SSAMC to find object. Comparing with tracker which use geometric transition dynamic model, we can say our proposed method can handle the problem quite good. Tracking object in low frame rate video is one of challenging issue, and we can handle it. Moreover, utilizing search window can help us to ensure our tracker track the correct object and the tracker be able to avoid unnecessary observations, and also only focus in a specific neighborhood around the sperm target.

For future work, there some parameter that we can tune. In PSO algorithm, we can explore the parameters which used

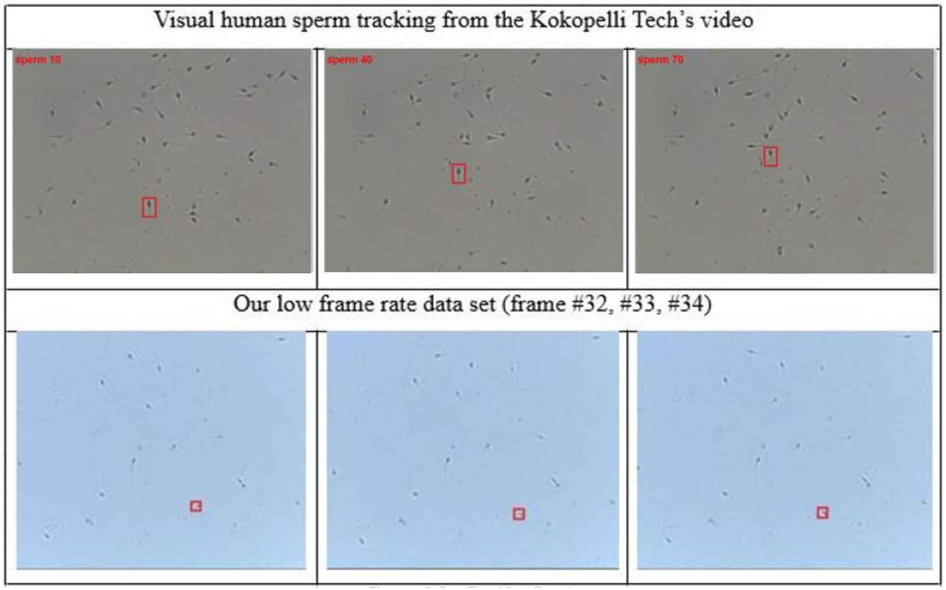

Fig. 4. Sample Result

in our implementation such as: random variable for individual and social component constant, and also number of particle and maximal iteration. In search window technique, it should be tuned carefully, because it has high dependency with data and frame resolution. Furthermore, if we choose the wrong size for search window, it can be decrease our proposed algorithm performance, so the precise size for search window is necessary to get optimal performance of our method. In the other hand, our proposed method only track single object, so multiple objects tracker need to be developed in the future, and generalizing of our tracker is possible to be applied in other research area like our other research [21].

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