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Design optimization of minimally invasive surgical robot

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ABSTRACT

In minimally invasive robotic surgery (MIRS), a surgeon teleoperates a robotic arm from a master console. This arm operates inside the patient's body through a small orifice which constrains the end-effector's translation along two axes. The workspace of such a robotic arm depends on its design as well as orifice location. Conventionally, the design of such an arm is optimized for large workspace and high dexterity. However, this large workspace might be reachable through only a few orifices, thus making the workspace volume and operation quite sensitive to the orifice location. To overcome this problem, we optimized the design of a 3 degrees of freedom serial robotic arm to attain multiple adjacent (desired number of) possible orifice locations, through which a planar workspace of pre-specified geometry can be traced. To achieve this goal, an algorithm was developed to relate the design of such an MIRS arm to the possible orifice positions. The optimization problem was solved using several metaheuristics such as simulated annealing, Tabu search, artificial bee colonization and genetic algorithm, and their performance was compared.

1. Introduction

Minimally Invasive Robotic Surgery *(MIRS) is an evolving field of research, accepted worldwide due to the advantages it provides over laparoscopic and conventional surgery. The first robotic surgery was done in 1985 with a PUMA robotic surgical arm for a neurosurgical biopsy [1]. Since then, many MIRS systems have been introduced, ranging from the first FDA approved surgical robot, ROBODOC to Computer Motion's Zeus [2] and Intuitive Surgical's da Vinci [3]. MIRS systems allow dexterous manipulation of surgical tools within the body cavity, through small orifices. This enables the surgeon to perform delicate and complex operations with increased vision, precision, dexterity and control [4] while causing minimum trauma, reduced blood loss and postoperative pain [5] to the patient. However, since the arm is restricted to operate through an orifice, a constraint is posed on its end-effector's translation along two axes. The volume of body cavity readily accessible to the surgical instrument (end-effector of the surgical arm) through the orifice is referred to as the 'reachable workspace' of the surgical arm.

Prime requirements for a surgical arm are large reachable workspace for increased tool dexterity and vision, and shorter links for less clutter and collision. In fact, both these requirements are coupled for such an arm. Location of orifice plays a critical role in determining these properties of the arm during surgery [6]. Conventionally, the design of robotic arms is optimized for large workspace and dexterity, neglecting the number of orifices through which these are achievable [7–9]. Hence, it might be the case that the desired volume of the reachable workspace is achievable through a very limited number of orifices. This leads to the requirement of additionally optimizing orifice location, such that the desired volume of workspace becomes reachable [6,10,11]. Also, due to the limitations of hardware or unmodelled noises, it might not always be possible to position the orifice at the optimized location with required accuracy and precision. This problem of high sensitiveness of workspace with respect to the orifice location can be reduced by choosing a design optimized for achieving the desired geometry of workspace through multiple adjacent orifice positions, instead of a single one.

Hence, the objective of this paper is to find the minimum optimal link lengths with which the desired numbers of such orifice positions – through which the end-effector can trace the workspace of desired geometry – are reachable for the MIRS arm. Since there is no relation defined between these two, we have proposed an algorithm for the same. This algorithm follows Monte

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Carlo approach and exploits the constraints posed by the orifice. It requires identifying and defining the workspace boundary, which were accomplished by using Monte Carlo method and Bezier curves, respectively.

The addressed optimization problem is a non-convex, constrained mixed integer non-linear optimization [12] problem. There has been a tendency to use metaheuristic approach to solve such problems [13,14]. We compared the performance of four such optimization techniques: Simulated Annealing (SA), Tabu Search (TS), Artificial Bee Colony optimization (ABC) and Genetic Algorithm (GA), for solving this problem for a simplified 3 degrees of freedom (DOF) serial robotic arm. Section 2 gives a background on these metaheuristics; Section 3 describes the method used for design optimization, workspace determination, boundary identification and the proposed algorithm for relating link lengths and number of candidate orifices. The results are discussed in Section 4 which is followed by conclusion.

2. Metaheuristic-based optimization

Design of general manipulators has been optimized using various metaheuristics such as genetic algorithm [15,16], simulated annealing [17], non-linear search optimization technique [18] etc. Metaheuristics are high-level strategies which guide the subordinate, more problem specific heuristic to reach global minima [19] such that the regions having superior solutions are identified speedily, preventing exploration of already traversed regions or those lacking better solutions. These metaheuristics can be categorized into two types on the basis of search strategy: population-based and trajectory-based [20]. To investigate the best suited metaheuristics for the current optimization problem, both these classes were explored by comparing performance of two algorithms of each type, namely, GA and ABC from population based, and TS and SA from trajectory-based metaheuristics.

Population-based algorithms have two important classes [21] – evolutionary algorithms [22] and swarm intelligence-based algorithms [23]. Evolutionary algorithms can process multiple solutions in parallel, eventually exploiting similarities in the set of possible solutions. GA is an evolutionary algorithm initiated with a randomly selected population of possible solutions (chromosomes) and improves over this population following principles of biological evolution and natural selection to result in the fittest solution [24–27]. Konietschke et al. [28] and Li et al. [16] used GA to optimize design parameters of MIRS arm to maximize the workspace. Swarm intelligence algorithms are inspired by collective problem-solving capabilities and properties expressing group behavior (like self-organization, robustness and flexibility) of social insects. Karaboga [29] introduced ABC algorithm, a swarm intelligence algorithm, which simulates the foraging behavior of honey bees. ABC does not have any history of application in robotic surgery, but has given significant results in other fields [30,31]. Trajectory-based metaheuristics differ from the population-based in the number of candidates searching for the best solution at a time. It initializes with a single candidate which explores the search space following a trajectory. TS was introduced by Glover [32,33] as a strategy to overcome local optimality by using memory structures. Applications of TS range from graph theory [34] to pure and mixed integer programming [32]. Though TS and SA are both trajectory methods, unlike TS which takes advantage of the history of the search space, SA is a probabilistic random search method with low memory requirements. SA [35] is motivated by the annealing process in condensed matter physics, according to which, if a solid is initially heated at a temperature sufficiently high to ensure random state and then cooled gradually to ensure thermal equilibrium, then the atoms will arrange themselves in minimum global energy crystal lattice. It has been comprehensively used in robotics [36,37]. Various researchers have compared the performance of these algorithms and have proved one to be better than the other in different conditions. Karaboga et al. [21] have shown that ABC produces better results in comparison to GA, PSO, DE, ES for optimizing various test functions. Battiti et al. [38] demonstrated that TS performs better than SA in terms of CPU time needed. In contrast to this, Paulli [39] reported that SA outperforms TS within same computation time. It is evident from these studies that performance level of optimization techniques varies with the problem. Thus, no direct conclusion can be made about which metaheuristic might befit the current design optimization problem. This motivated us to compare the performance of the four algorithms for this problem.

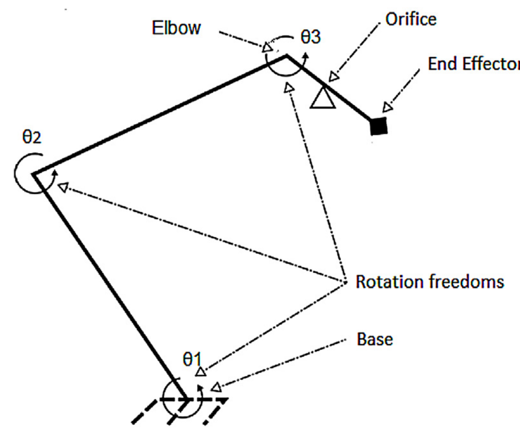

Fig. 1. 3 DOF surgical robotic arm.

3. Methods

For computational simplicity, a planar robotic arm consisting of 3 rotational joints (3 DOF) (Fig. 1) is considered here. The surgical instrument is represented by the end effector which is attached to the far end of the arm. Since the arm operates in a planar workspace, the orifice poses a constraint on the translation of the end-effector along only one direction, thus leaving one rotation and one translational degree of freedom.

The objective of the current optimization problem is twofold: minimizing link lengths, which are continuous variables and achieving desired number of valid orifice locations, which can take only integer values, and hence it is a mixed integer non-linear optimization problem. Since the variables are bounded and there can be multiple such link lengths and valid orifice locations count combinations, the problem is constrained and non-convex. This optimization problem can be mathematically formulated as:

$$\min_{\vec{L}} \left(r - f_e(\vec{L})\right) \quad (1)$$

Such that: $\sum_i |L_i| \leq \in$

where, r represents the desired number of valid orifice locations, i iterates over the links and $\in$ represents the maximum limit of the sum of length of the links. $f_e(.)$ follows the proposed algorithm for evaluating the number of valid orifice locations (e) with current link lengths, $\vec{L}$.

The process of obtaining e for the given design parameter $\vec{L}$ can be summarized as follows:

1. Calculate elbow workspace W_{elb} corresponding to the current kinematic configuration of the robotic arm.
2. Identify the boundary region B for workspace W_{elb}.
3. For each location p in W_{elb}: