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# The Application of Adaptive Filters for Motion Prediction in Visually Tracked Laparoscopic Surgery*

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***Abstract* – More and more research teams propose robotic systems to control the position of the laparoscope. In many of them the visual tracking principle is applied. However as experiments have shown tracked markers may often be obscured during a surgery. Within the article a study on the possibility of the application of a predictive algorithm to anticipate the position of a chirurgical tool is presented. This system would generate an estimate of the position whenever tracked tool's marker is obscured. As its basis the LMS algorithm was chosen, to which supplementary modifications were introduced. Experimental simulations prove that the algorithm greatly reduces the amount of missing samples during real time operation. Obtained predicted positions of the chirurgical tool reasonably approximate its true position.**

***Index Terms* – *adaptive filtering, laparoscopic surgery, motion prediction***

## I. INTRODUCTION

Current trends in surgery involve the minimization of the number and size of cuts in order to reduce the time of recovery of a patient. The key technique involved is the laparoscopic surgery, in which the surgeon operates on organs inside patient's body, by inserting special chirurgical tools and observing their tips' positions via a camera, which is usually held by an assistant. This method has several drawbacks, for example the displayed image may be affected by assistant's hand tremor causing the details to be blurry or the occurrence of misunderstandings between the surgeon and his assistant. Research teams have been trying to eliminate these in a number of ways, usually replacing the assistant with a robotic arm holding the laparoscope. Still however the problem of robot control remains. Several solutions have been presented so far. They include joysticks, feet operated controllers, visual identification of surgeon's head motion [1] or most recently tracking of chirurgical tools by means of optical or radio systems [2]. The latter ones utilize so obtained data in order to control the position of the laparoscope as the function of relative positions between instruments and the tip of the laparoscope. In any such system a problem arises how to react whenever instruments' position data is not being fed to the robot control circuitry. Such a situation may often arise when visual tracking systems are used. During an operation obscurity of markers may result from a number of events, starting from an abnormal or extreme positioning of the tracked tool by the surgeon, ending with involuntary disturbance caused by for example a nurse performing her duties or any other person present at the operating theatre. Usually in such cases the period during which the marker is not tracked does not exceed a few seconds (Fig. 1), hence we may try to make an educated assumption on where the tool could have been placed at that time, based on our prior knowledge of the characteristics of tool's motion. The above problem, even though similar to that stated in [3] - [5] is altogether different, since signals to be predicted display very small degree of periodicity.

In this paper we study the possibility of the application of signal prediction techniques in order to approximate the position of the marker whenever the real data is not available. The algorithm description will be given as well as experimental results of laboratory trials and experiments be presented.

## II. ADAPTIVE FILTERING

The problem of signal prediction is well known in the domain of signal processing and basically consists in making an assumption on the value of the signal's future sample based on its past knowledge [6]. This statement of the problem

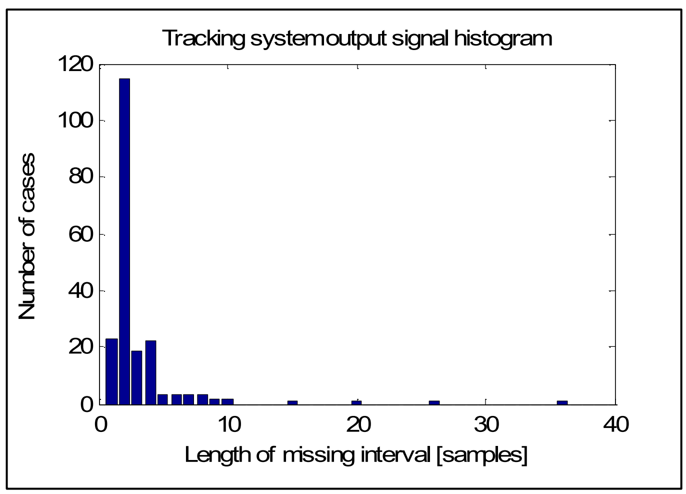


Fig. 1 Histogram of the tracking system output signal. Sampling frequency is equal to 10Hz.

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makes the application of an adaptive filter an ideal solution. In this case we have a digital linear filter of length $N$, which coefficients $A_{p-1}(t)$ take $N$ past values of the input signal $X_{p-1}(t)$, each with a weight $a_i$ and aims at approximating the current value of the signal $x_p(t)$. The difference between these two values $e_p^{1\to p-1}(t)$ is then used in order to update filter coefficients (Fig. 2), so as to minimize the prediction error. The exact solution to the problem of filter coefficients' adjustment is given in the form of Weiner-Hopf equations.

$$A_{p-1}(t) = R_{p-1}^{-1}(t) S_{p-1}(t) \tag{1}$$

Where: $R_{p-1}(t) = E\left[X_{p-1}(t) X_{p-1}^{*}(t)\right]$ (2)

$$S_{p-1}(t) = E\left[X_{p-1}(t) x_p^{*}(t)\right] \tag{3}$$

$X_{p-1}(t)$ - vector of the past samples of the signal,
$x_p(t)$ - present sample of the signal.

This approach, even though most precise has a very limited applicability, since if introduced to any real time system it would require powerful DSP processor in order to perform the real time inversion of the matrix $R_{p-1}(t)$. In order to account for this limitation certain approximation was introduced that led to the least-mean-square (LMS) adaptive algorithm. Due to its simplicity and efficiency it has become extremely popular in telecommunications and digital signal processing. It not only eliminates the matrix inversion problem, but allows to express the updated linear filter coefficients values as a function of previous filter coefficients.

The LMS algorithm is composed of two steps, firstly we compute the prediction error of a given sample

$$e_p^{1\to p-1}(t+1) = x_p(t+1) - A_{p-1}^{*}(t) X_{p-1}(t+1) \tag{4}$$

And then use the obtained result (4) to update filter coefficients:

$$A_{p-1}(t+1) = A_{p-1}(t) + \delta \cdot \left(e_p^{1\to p-1}(t+1)\right)^{*} X_{p-1}(t+1) \tag{5}$$

In the above equation the step-size parameter $\delta$ is responsible for the sensitivity of the filter to rapid changes at the input. In order to assure stability, according to [7] it can assume the following values:

$$0 < \delta < \frac{2}{3NP_x} \tag{6}$$

Where: $P_x$ – signal power

When entering the prediction mode, and no true signal is available we assume that the approximate position is simply obtained by filtering most recent signal samples through the filter with most recently updated filter coefficients:

$$x_{pred}(t) = A(t) \cdot X_{lkv} \tag{7}$$

Where: $X_{lkv}$ – vector of the last known true signal values

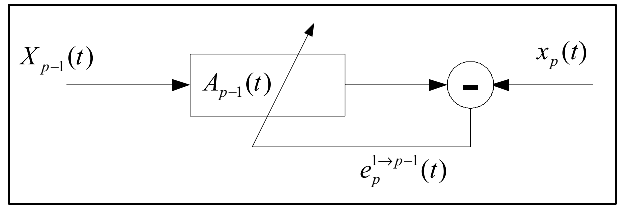


Fig. 2 Adaptive filter as a signal predictor.

If however we are to provide more than one sample, this would mean, that having determined the first one the prediction error is equal to zero and no filter coefficients update is performed. This results in obtaining a constant prediction output. In order to prevent this case we suppose that the prediction is performed with a certain error, which is artificially generated. The error generator characteristics is such that the output is as similar to the prediction error signal, when the true samples are present. This means the average $\mu$ and standard deviation $\sigma$ of both, true and artificially generated prediction error have to be the same. More importantly however we also need to account for the spectral similarity of both signals. Computer generated random numbers cover all range of frequencies, whereas in the real prediction error signal low frequencies are dominant. This is why, the artificially generated error is in fact obtained by filtering randomly generated numbers with a low-pass Butterworth filter.

$$e_p(t) = \sum_{j=0}^{M} g_j v_{p-j}(t) + \sum_{k=1}^{M} h_k e_{p-k}(t) \tag{8}$$

Where: $g_j$, $h_k$ – digital Butterworth filter coefficients
$M$ – Butterworth filter length
$v$ – normal random variable N~($\mu,\sigma$)

Then this artificial prediction error (8) is introduced into equation (5) enabling filter coefficients update, and consequently removing the constant output problem. This approach is very similar to that of the ARMA signal model, where the signal sample may be approximated by a linear combination of past samples and linear combination of white noise. However instead of a IIR filter a FIR filter on a white noise is used:

$$x(n+1) = \sum_{m=0}^{M} f_i x(n-m) + \sum_{p=0}^{P} g_p v(n-p) \tag{9}$$

Where: $f_m$, $g_p$ – weight coefficients
$M$, $P$ – integers
$v$ – white noise N~(0,1)

## III. Motion Prediction Algorithm

In order to fully determine the position of an object in a three dimensional space one needs six variables: x, y, z – coordinates of the marker in space, $Q_x$, $Q_y$, $Q_z$ – rotation of the marker along reference axes. All these values are provided by the tracking system. In order to simplify the problem we may predict each of these coordinates independently as a one dimensional signal. Consequently for each tool, which position we want to track and predict we need six one dimensional LMS algorithm based signal predictors.

The system was designed in such a way, that as long as the true signal is present, its values serve to update the adaptive filter coefficients. If the tracking system raises a flag, that the marker is missing, the approximate position will be calculated (Fig. 3). Even though the core part of the motion predictor is the LMS adaptive algorithm some additional modules have been added in order to improve the functioning of the system.

During the calibration the maximal and minimal value of the signal is determined thus creating the ‘operation volume’ in which, we assume, all future values will be contained. In this way we impose certain limits on the range of predicted values as well make sure that at the output of the LMS algorithm we will not obtain unrealistically high or low numbers. Moreover whenever the signal leaves the operation volume we may stop both, prediction of values if the signal is considered missing, or refrain from updating adaptive filter coefficients with unrealistic coordinates. Since as the operation draws to the end surgeon usually slightly changes the operation volume, the minimal and maximal values of the signal can be updated, however only if the real signal leaves the operation volume at a sufficiently small velocity.

While operating it is normal for the surgeon to pull out and replace chirurgical device he is using. Usually it is then placed on a table not far from the patient, often still inside the tracking system’s camera operation volume. In such a case the system would adapt the LMS filter to a set of data for which we are not interested in predicting data. Since there is no need to predict the position of the tool outside patient’s body. In such a case the system would not need to perform any operations and prediction might be temporarily turned off.

In order to be able to determine when the tool leaves the operation volume because of being pulled out, rather than purposely moved out of the operation volume we calculate the velocity of the motion. If it attains a value larger than the maximal one determined during the calibration procedure, it means that an ‘abnormal’ motion, such as removal of the tool from patient’s body, is being performed by the surgeon, and if at the same time the tool leaves the operation volume the system might turn the prediction off. The velocity delimiter also works when in the prediction mode, forcing predicted samples not to have a larger rate of change than the one determined during calibration.

Using the LMS algorithm may lead to obtaining a long sequence of strictly increasing or decreasing numbers. This case is not natural during a operation and rarely may be observed. In order to avoid such a situation when the position is being predicted we compare the signal current trend with the probability of the trend to continue, which is determined during the calibration. If this probability is very low, then the predicted sample is forced to change its value in such a way, that the trend is being opposed.

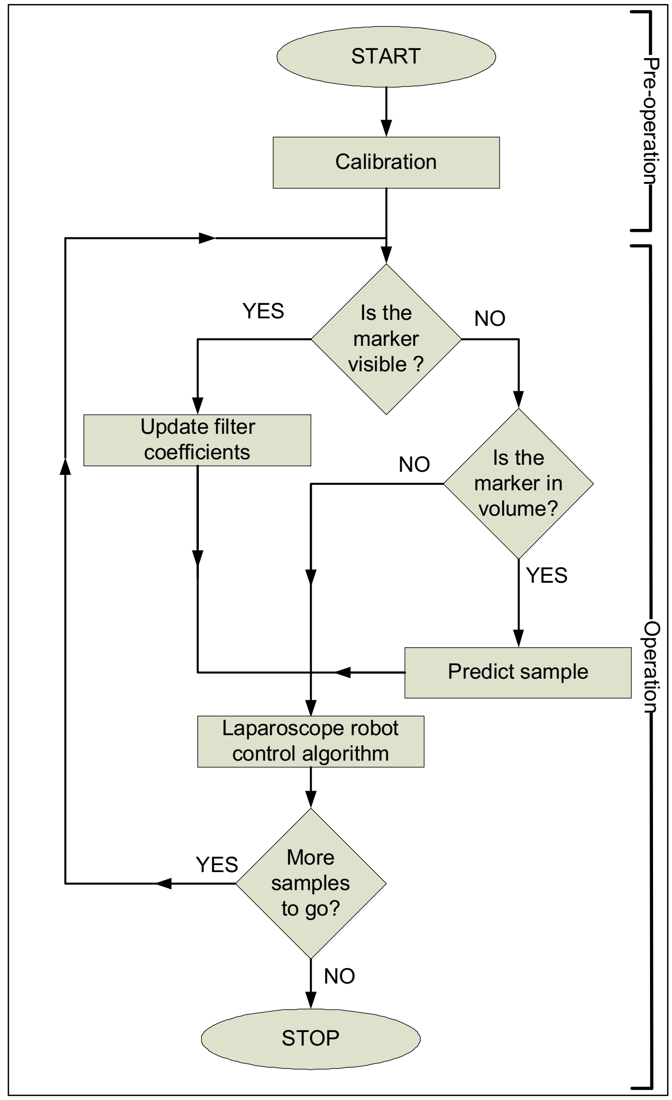


Fig. 3 Outline of the prediction algorithm.

## IV. Experimental results

In order to verify the system in practice a number of tests was performed. They included a simple simulation of a procedure with the use of a laparoscope performed by a surgeon on a laboratory stand (Fig. 4). It consisted in the removal of the gallbladder from a prepared sample pig organ placed in the training box. The laboratory stand was equipped with an Intel Core 2 Duo 2,4 GHz processor PC, on which the program was running in Matlab environment. As the tracking system Polaris Accedo by NDI was used. This system requires software predefinition of the physical structure of a marker, which has to be composed of at least three reference points. Each reference point is a small sphere covered with a highly reflective material. Having located positions of a sufficient number of reference points the tracking system is capable of determining the position of the origin of the marker in the coordinate system and its rotation. It is then expressed by seven parameters, translational ones x, y, z, and rotation expressed as a quaternion: $q_0, q_x, q_y, q_z$ . As long as a sufficient number of reference points of a marker is visible the position of the origin of the marker in the numerical form can be obtained, otherwise a 'missing' codeword is sent. The prediction algorithm deals with the prediction of the position of the origin of a marker and does not include predicting the position of markers' individual reference points.

In order to be able to gather real position data and test the predicting algorithm at the same time a dual marker was designed and attached to the top of the instrument. It consisted of two markers joined together. The first one was a six point marker which was much less likely to be lost by the tracking system, due to the number and placement of reference points. It was enough to have at least half of its points visible in order to be able to determine its location in the coordinate system. The position of this reference marker was assumed to be true and would be used in the assessment of the quality of prediction of test marker's position. The test marker, on which the prediction algorithm was checked, was a simple 3 point marker. It was really easy to lose it out of sight, since in order to determine its position, all of its three points had to be visible to the system. During the experiment this marker would very likely be invisible to the tracking system, while the reference one not. Consequently a comparison between position predictions and real data would be possible.

The experimental procedure was not overcomplicated. Firstly the calibration needed to be performed, which involved acquiring 256 samples of preferably continuous signal. Having determined all necessary parameters the operation could start.

The first experiment involved the simplest case possible that is a hand held chirurgical tool aimed to be maintained in approximately constant position. Slight offset between the position of test and reference markers is of the order of 0.2 mm, which in this case is of the order of the precision of the measurement system. In general however it may originate from misalignment of reference systems of both markers. During the experiment one of the points of the test marker was covered from time to time in order to enter the prediction mode. The results prove that the predictive algorithm provides a reasonable approximation of the position (Fig. 5). Even though the lines do not overlap, the difference between them is minimal.

The more challenging task involved predicting the position of the tool when it was in motion. This was achieved by simulating an operation performed by a surgeon on pig organs. As expected there was a large number of short intervals when the test marker was missing, allowing to test the applicability of the signal prediction algorithm in real environment.

The results of the accuracy of the prediction are presented in the form of a histogram (Fig. 6), of differences between reference and predicted signals. In majority of cases attained precision is rather high, of the order of several millimetres. Of course as we try to predict the signal for larger intervals of time on average it tends to diverge from the true one (Fig. 7). This behaviour is expected, since we may find it much harder to make an educated guess on the surgeon's tool position after 10 or 20 seconds. The decrease of the RMS prediction error for larger time spans may not be interpreted as the improvement of the prediction quality. It is a result of having insufficient number of test data for such long intervals.

Experiments have also proven that real time prediction is possible. The average sampling frequency obtained during tests was of the order of 10-12Hz, which is similar to that used in control system described in [2].

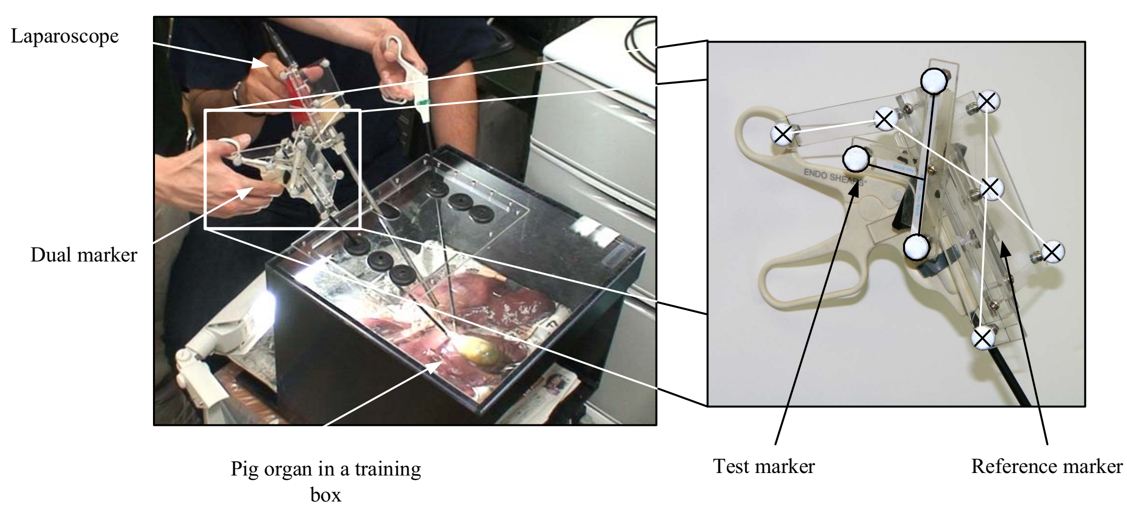


Fig. 4 Overview of the laboratory stand. Training box viewed from the position of Polaris tracking system. Dual marker enlarged in the right hand figure.

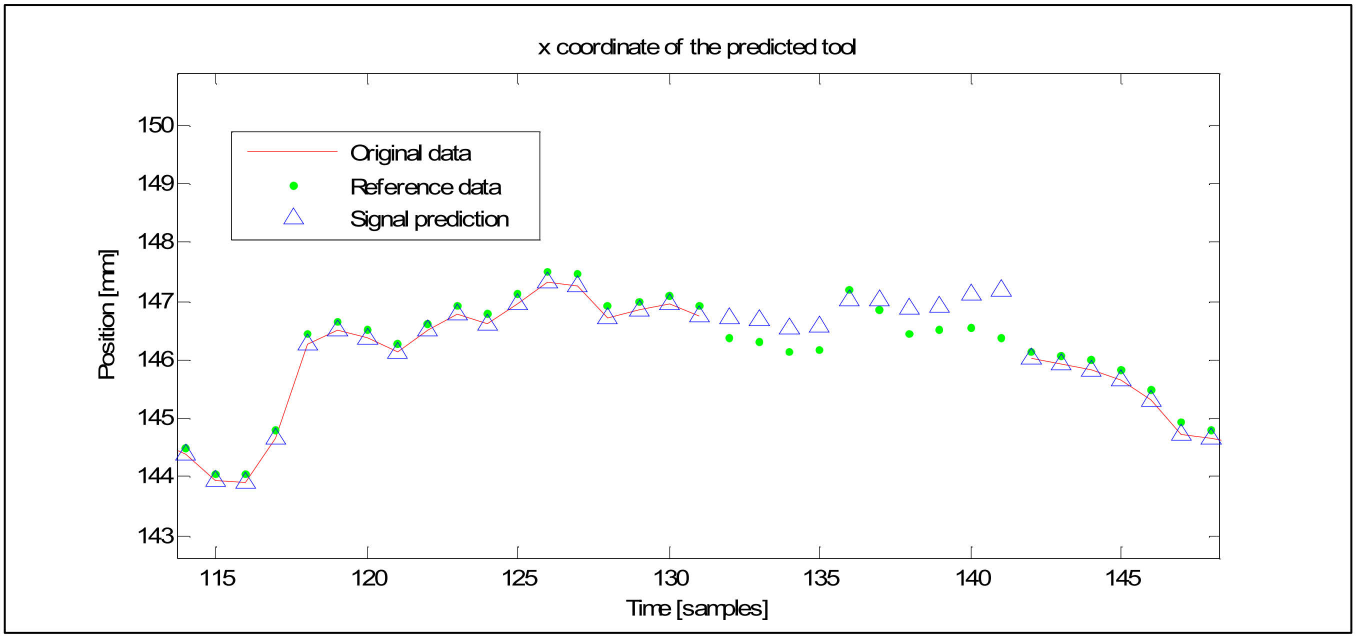


Fig. 5 Example of position prediction, when tool was held in hand at a fixed position.

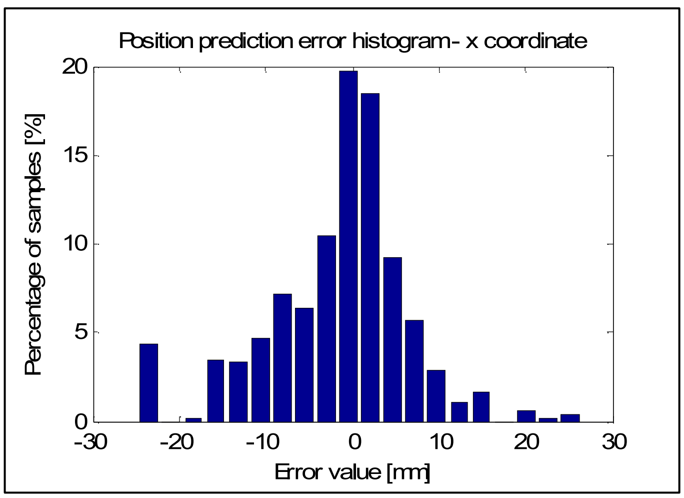


Fig. 6 Histogram of prediction error values as the difference between the prediction and the reference signal during the operation.

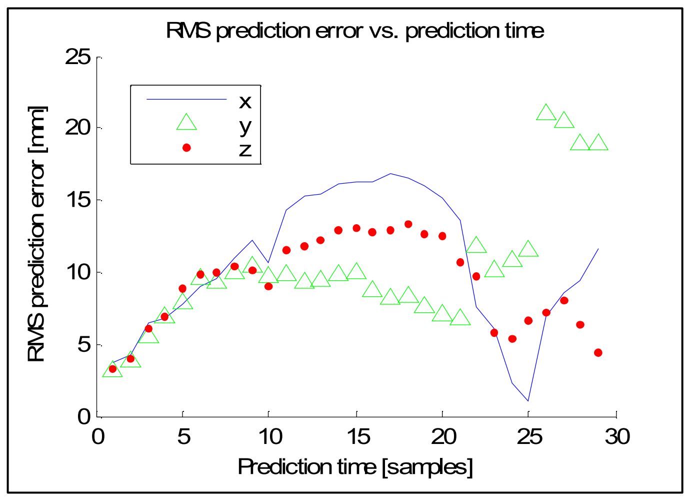


Fig. 7 Dependence of the RMS error on the prediction time for data obtained during the operation.

## V. Conclusions

In the above article a system dealing with the problem of obscured marker location for visually tracked tools has been presented. As the proposed solution an adaptive filter as a signal predictor, with a modified LMS algorithm was applied. It allows to completely eliminate missing samples and discontinuities from signals describing positions of chirurgical tools, which can be obtained for example via visual tracking. Laboratory tests have shown, that this system may be applied in real time and most importantly provides a reasonably accurate approximation of markers' position. Not surprisingly however the quality and accuracy of prediction decreases as the prediction interval increases. The further research would involve implementation of the algorithm into a laparoscopic robot control program and tests, where feedback from surgeon could be obtained.


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