Prediction of Missing Markers in Motion Capture System

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***Abstract*—This paper presents the results of the project assignment that was conducted for the course "Applied estimation" at KTH, Stockholm. The paper addresses the problem of real-time tracking of autonomous vehicle in the presence of missing data. The data is 3d marker positions from a motion capture system. Each marker must be visible to at least two cameras in each frame in order to unambiguously establish its position. This is not always the case which leads to occlusion of markers in the system. This can result in significant problems in tracking accuracy unless a continuous flow of data is guaranteed. In order to provide a continuous stream of data and hence to improve 3D real-time motion capture, a prediction algorithm is proposed. The method uses an extended Kalman filter approach and pre-defined distances between marker to estimate the position of the object. The suggested method behaves well for a reasonable number of frames, when markers are missing with in two seconds interval.**

I. Introduction

Optical motion capture (MoCap) system is a tracking system widely used in application fields such as computer animation and video games [3], biomechanics [4], or medicine [5].

Optical motion capture is a technology used to turn several camera observations of a moving subject into 3D position and orientation information about that subject. Markers are attached to the subject which is being recorded, the location and movement of the identified markers is then used to infer the movement of the subject [7]. Each marker must be visible to at least two cameras in each frame in order to unambiguously establish its position. An ideal 3D trajectory for a marker lasts for the whole sequence from the start of tracking to the end of tracking. However, this is usually not the case, trajectory is broken when the marker is occluded or the algorithm confuses one marker with another resulting in position of the marker to be missing or lost in the tracking system. This temporary loss of data is a significant problem in marker-based motion capture systems. Markers may often disappear by moving out of the camera view or they are blocked by an object and are failed to be seen by the camera. Absence of a marker also happens when the feature is not measured due to sensory error. If enough cameras do not see a marker, triangulation becomes impossible and the 3D position cannot be calculated. Usually, increasing the number of cameras mainly reduces occlusion effects while also improves accuracy and coverage, however this approach is not always possible [6]. Although many methods have been developed to handle the missing marker problem, most of them are not applicable in real-time and often require manual intervention [7]. Method described in the paper can be used in real-time for estimating the position of occluded markers using extended Kalman filter approach and taking advantage of the fact that for markers on the vehicle the intermarker distance is approximately constant. Thus, the neighbouring markers provide us with useful information relevant to the current position of the non-visible marker or markers. Results demonstrate that the method presented effectively recovers, a good estimate of the true positions of the missing markers, when one or two markers are occluded for a long period of time. When three markers are missing for a short period of time the method gives good estimations as well. However, for estimations of all three markers for the longer period of time a further work needs to be done. All the equipment and setup to carry out the work was provided to us by the team in "The Automatic Control Project Course - EL2421" which is offered at KTH - Royal Institute of Technology.

II. Related Work

In order to solve the issue of missing markers, and recover data in optical motion capture system, a number of methods have been proposed. Those methods can be divided into two types, off-line procedures to be used in post-processing and methods to be used in real-time.

Some commonly used off-line methods, interpolate data using linear or non-linear approaches [8] [9]. Interpolation require data sampled before and after occlusion, and therefore cannot be used in real-time applications. Some Motion Capture systems also provide missing marker recovery solutions using interpolation techniques in combination with kinematic information. Off-line approaches also include model based methods. Rhijn and Mulder et.al proposed a geometric skeleton based approach to bridge existing gaps in the measured data series. The system automatically constructs the geometric skeleton structure, degrees of freedom (DOF) relations, and DOF constraints between segments. This is done in a so-called ”model estimation phase”, an offline procedure. in which a set of body parts is put through all possible motions to determine the movement constraints imposed by the joints. The tracking method uses the obtained device model to recognize the device and reconstruct all DOF parameters describing the pose of each segment [10].

Real-time approach is using extrapolation algorithms, which only require data sampled before an occlusion and thus can be used on real time. Piazza et al. [11] suggests an extrapolation algorithm partly combined with a so-called constraint matrix in order to bridge sampling gaps caused by occluded markers. It predicts the marker position based on previous position and velocity, using the assumption that movement can be linear, circular, or a linear combination of both. This prediction is corrected using a constraint matrix, storing rigid marker distance relations. Real-time approaches to recover motion data also include predicting measurement state using Kalman filter or various non-linear versions of it. Aristidou et al. [7] presents a prediction algorithm, which uses a Kalman filter approach in combination with inferred information from neighbouring markers. Tak and Seok. Ko et al. [12] propose a methods that uses Unscented Kalman filter to handle the nonlinearity in the dynamic constrains more accurately, without using Jacobian-based approximation. Unscented Kalman filter output is then processed using a least-squares curve fitting technique, to restore the relationship that existed between the position, velocity, and acceleration values describing the motion before the filter was applied. Dorfmuller [13] uses an extended Kalman filter (EKF) to predict the missing markers using previously available marker information while Welch et al. in [10] used an EKF to resolve occlusions based on the skeletal model of the tracked person. Wu.Q and Boulanger P et.al [15] use Kalman filter to estimate missing marker position, and then reconstruct human motion within a simple extrapolation framework. Some real-time approaches made prediction based on other quality measurements such as fixed inter-marker pairwise distances[16] . By tracking a the movement of the markers, one can identify temporarily occluded markers based on characteristic fixed inter-marker distances. This approach may become ineffective when all or a significant number of markers are missing. Our method uses Extended Kalman filter in order to better handle the nonlinear dynamics of the process. Filter runs all the time and gives estimates of the position of the truck. When occlusion occurs we take advantage of fixed inter-marker distances. Thus, in the case of a missing marker, its position can be recovered through the distance constraints imposed by markers.

III. Environment setup

Motion Capturing System from Qualisys Qualysis[1] was used to track the markers. The system does a multiview 3D construction of passive IR markers. The system is based on the fact that if a point in space is seen from at least two different viewpoints with calibrated cameras of known position the position of the point in 3D can be calculated. Position of each marker is computed from 2D images of four tracking cameras of the Qualisys. Cameras are mounted in each corner of the room and in a circular setup. The speed of the MoCap system was set to 10 Hz (100 frames per second). The object to be tracked was TAMIYA Scania truck, has three static markers attached on top of it, in irregular triangle structure and can be seen below.

Fig. 1. Truck which was used in the experiment with three markers attached to it.

Markers used were small reflective balls which are seen in the camera image as bright dots. Three markers are used since three points are needed to define position

[1]www.qualysis.com

and rotation in 3D. Placing more markers can result in better tracking results (assuming errors without bias) as not all markers have to be visible all the time and that way decrease the possibility of occlusion. This however also increases the possibility for markers to merge and risk for ambiguity. Therefore adding more markers was unfortunately not an easy solution to improve tracking reliability.

A. Data collection

Several test where performed in which the markers were occluded for different amount of times in different areas of the patch while the truck was following one path around the room. This was done in order to establish where markers can go missing and the length of occlusion. Different types of motion were tried in order to a get a better prediction of the process model of the vehicle and be able to find a model that can generalize well to different types of motion. The trucks are controlled with 10 Hz due to the limited capacity of the wireless connection and therefore the information used from the MoCap could only be used for every 100 millisecond instead of 10 milliseconds in order to match the control data.

IV. The Tracking Method

The method is an improvement based on the data acquired from the optical motion capture system, and the kinematic model used to describe the behavior of the truck.

A. Rigid Body Tracking

With the truck moving on a planar surface, it is sufficient enough to only track its 2D position. Three static markers are attached to the truck (M_1, M_2 and M_3), the position P of the vehicle can be seen as the linear combination of the markers

$$P = \alpha M_1 + \beta M_2 + \gamma M_3 \tag{1}$$

where P and M has a x and y component and α, β, and γ are the unknown linear constants. This system is underdetermined system with three unknowns and two equations. Usually, such a system has infinitely many solutions. In order to find a single unique solution for α, β, and γ, we simply added an extra third component $z = 1$ to P and M. So, an extra constraint has been made in the form of $1 = \alpha + \beta + \gamma$. Equation (2) can then be rewritten as

$$\begin{pmatrix} P_x \\ P_y \\ 1 \end{pmatrix} = \alpha \begin{pmatrix} M_{1,x} \\ M_{1,y} \\ 1 \end{pmatrix} + \beta \begin{pmatrix} M_{2,x} \\ M_{2,y} \\ 1 \end{pmatrix} + \gamma \begin{pmatrix} M_{3,x} \\ M_{3,y} \\ 1 \end{pmatrix} \tag{2}$$

Rearranging equation (2) in matrix multiplication form

$$\begin{pmatrix} P_x \\ P_y \\ 1 \end{pmatrix} = \begin{pmatrix} M_{1,x} & M_{2,x} & M_{3,x} \\ M_{1,y} & M_{2,y} & M_{3,y} \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \\ \gamma \end{pmatrix} \tag{3}$$

Solution for α, β, and γ is of the system can be obtained using the inverse matrix of the coeffcients.

$$\begin{pmatrix} \alpha \\ \beta \\ \gamma \end{pmatrix} = \begin{pmatrix} M_{1,x} & M_{2,x} & M_{3,x} \\ M_{1,y} & M_{2,y} & M_{3,y} \\ 1 & 1 & 1 \end{pmatrix}^{-1} \begin{pmatrix} P_x \\ P_y \\ 1 \end{pmatrix} \tag{4}$$

This method of calculating the truck's position only works if all markers are identified. Establishing the position of the vehicle in case of the marker occlusion will be covered in section E which describes the observation model.

B. Extended Kalman Filter

Extender Kalman filter is a popular estimation technique and has been largely investigated for state estimation of nonlinear systems.[17] The EKF consists of using the classical Kalman filter equations to the first-order approximation of the nonlinear model about the last estimate. The process model has a state vector x $\in$ R^n and is governed by the non-linear stochastic difference equation

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \tag{5}$$

with a measurement z $\in$ R^m that is

$$z_k = h(x_k, v_k) \tag{6}$$

where random variables w_k and v_k independent of each other variables w$_k$ and v$_k$ represent the process and measurement noise (respectively). They are assumed to be white, and with normal probability distributions

$$p(w) \sim N(0, Q)$$
$$p(v) \sim N(0, R)$$

where Q is process noise covariance and R is measurement noise covariance. The non-linear function f in the difference equation (5) relates the state at the previous time step *k*-1 to the state at the current time step *k*. Along with the noise it also sometimes includes any driven function u_{k-1}. The non-linear function in the the measurement equation (6) h relates the state x_k to the measurement z_k. Since in practice individual values for the noise v_k and w_k at each time step are not known, one needs to approximates the state and the measurement vector without those values as:

$$\bar{x}_k = f(\hat{x}_{k-1}, u_{k-1}, 0) \tag{7}$$

and

$$\bar{z}_k = h(\bar{x}_k, 0) \tag{8}$$

where $\hat{x}_k$ is some a posteriori estimate of the state (from a previous time step k). To estimate a non-linear process model and non-linear measurement model, we begin by writing new governing equations that linearize an estimate about (7) and (8).

$$x_k = \bar{x}_k + A(x_{k-1} - \hat{x}_{k-1} + w_{k-1}) \tag{9}$$

and

$$z_k = \bar{z}_k + H(x_k - \bar{x}_k + v_k) \tag{10}$$

where x_k and z_k are the actual state and measurement vectors and $\bar{x}_k$ and $\bar{x}_k$ are the approximate state and measurement vectors from (7) and (8) and $\hat{x}_k$ is an a posterior estimate of a state at step k. A is the Jacobian matrix of partial derivatives of f with respect to x, that is

$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[j]}}(\hat{x}_{k-1}, u_{k-1}, 0) \tag{11}$$

and H is the Jacobian matrix of partial derivatives of h with respect to x,

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}}(\bar{x}_k, 0) \tag{12}$$

The equations for the Extended Kalman filter fall into two groups: time update equations and measurement update equations. Time update equations used in Extended Kalman filter project the state and covariance estimates from the previous time step *k-1* to *k* to the current time step and are described in Table l below. The measurement update equations in Table ll , are responsible for the feedback - correct the state and covariance estimates with the measurement z_k into the a priori estimate to obtain an improved a posteriori estimate. We define $\hat{x}_k^-$ (note the "super minus") to be

TABLE I
EKF TIME UPDATE EQUATIONS

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0) \tag{13}$$

$$P_k^- = A_k P_{k-1} A_k^T + Q_{k-1} \tag{14}$$

our *a priori* state estimate at step *k* given knowledge of the process prior to step *k*, and $\hat{x}_k$ to be our *a posteriori* state estimate at step *k* given measurement z_k. P_k^- is *a priori* estimate error covariance.

TABLE II
EKF MEASUREMENT UPDATE EQUATIONS

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k) \tag{15}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-, 0)) \tag{16}$$

$$P_k = (I - K_k H_k) P_k^- \tag{17}$$

The estimate of the new state given prediction and correction from observations is then given in equation (16). The Kalman gain K between actual and predicted observations is represented in equation (15). The Kalman gain K is chosen to minimize the steady-state covariance of the estimation error given Q and R. Finally, (17) is used to calculate the error covariance matrix of the updated estimate.

C. Process Model

The model of the truck was obtained using the basic kinematics of vehicle motion. The pose is defined by its position (P_x, P_y) and the orientation θ. The actuations are the velocity of the vehicle *v* and the angle of the wheels is given by φ. The only parameter is the length between the rear and front wheels *l*. The predicted the change in translation $\frac{d}{dt}(P_{t,x}, P_{t,y})$ and in direction $\frac{d}{dt}P_{t,\theta}$ (angular velocity) for the truck is described in equation (18), below .

$$\bar{u_t} = \frac{d}{dt}\begin{pmatrix} P_{t,x} \\ P_{t,y} \\ P_{t,\theta} \end{pmatrix} = \begin{pmatrix} v_t cos(P_{t-1,\theta}) \\ v_t sin(P_{t-1,\theta}) \\ tan(\varphi)/l \end{pmatrix} \tag{18}$$

Since the MoCap system is not able to measure the steering angle φ, angular velocity of yaw $\frac{d}{dt}\theta$ was measured. This is the main reason that we need to relate these calculates to yaw, instead of the steering angle. Both the velocity v_t and $\frac{d}{dt}\theta$ were experimentally modeled using $u_{throttle}$ control signal and $u_{steering}$ steering signal. This was done by measuring and plotting the velocity against throttle control signal and $u_{steering}$ to $\frac{d}{dt}\theta$. Two linear models to approximate velocity and orientation were found and are shown below in equation (19) and (20).

$$v_t = h \cdot \tilde{u}_{throttle} + m \tag{19}$$

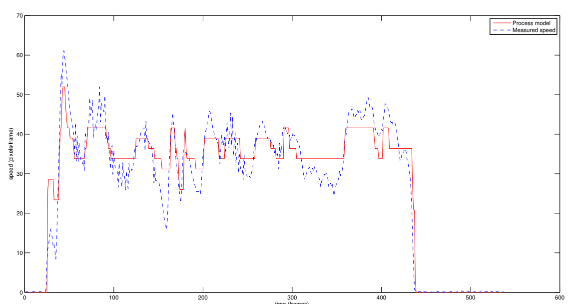
$$\frac{d}{dt}\theta_t = k \cdot \tilde{u}_{steering} + n \tag{20}$$

There is a transport delay on both control signal and steering signal due to using wireless communication and is situated between the concerned T-mote pair. The delayed control signal and steering signal are represented as $\tilde{u}_{throttle}$ and $\tilde{u}_{steering}$, respectively. Linear models were tested on different types of data, we decided not to overfitt the model, but have a more general model which can still give good approximation. Parameters used in equation (19) and (20) were chosen according to that goal and are shown in the table below.

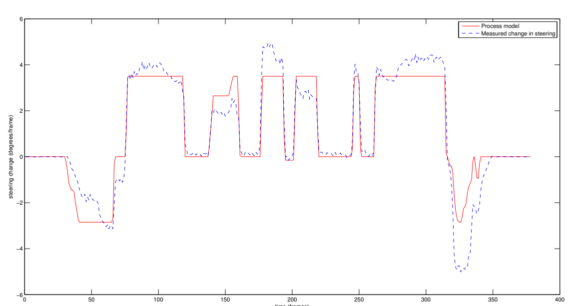
TABLE III
PARAMETERS FOR THE PROCESS MODEL

Parameter	Information
delay for the throttle signal	delay with 4 frames
delay of the steering signal	delay with 2 frames
h	2.60
m	-163.77
k	-0.05
n	3.50

Models of the velocity and $\frac{d}{dt}\theta$ compared with measured values are shown in Figure 2.



(a) Modeled translation velocity vs measured translation velocity.



(b) Modeled angular velocity vs measured angular velocity.

Fig. 2.

D. Observation model

Observation model used is the position of the markers which gives 3D position and orientation information about the vehicle. Due to the hardware properties of the sensor used for motion capture (MoCap) the measurements tend to be noisy. Therefore the position and orientation information computed by the Mocap have noise in them and are approximations. When occlusion is detected by the observation model, information from the neighbouring marker/markers is used to approximate the position of a missing marker/markers.

1) One marker is missing: Using the fact that the distance $d_{i,k}$ and $d_{i,l}$ between occluded marker M_i and visible markers M_k and M_l are approximately constant and obtaining the heading direction θ, we can approximate the position of the missing marker.

$$M_i^k \approx \begin{bmatrix} d_{i,k}cos(\theta_{i,k}) \\ d_{i,k}sin(\theta_{i,k}) \end{bmatrix} + M_k \tag{21}$$

$$M_i^l \approx \begin{bmatrix} d_{i,l}cos(\theta_{i,l}) \\ d_{i,l}sin(\theta_{i,l}) \end{bmatrix} + M_l \tag{22}$$

Then taking the average from those approximated positions, we calculate the position of the occluded marker.

2) Two markers are missing: Similar, by knowing the heading and the distance $d_{i,k}$ and $d_{i,l}$ between occluded marker M_i and M_k and visible marker M_l we can reconstruct the approximated position of the missing markers.

$$M_i^l \approx \begin{bmatrix} d_{i,l}cos(\theta_{i,l}) \\ d_{i,l}sin(\theta_{i,l}) \end{bmatrix} + M_l \tag{23}$$

$$M_k^l \approx \begin{bmatrix} d_{k,l}cos(\theta_{k,l}) \\ d_{k,l}sin(\theta_{k,l}) \end{bmatrix} + M_l \tag{24}$$

3) All markers are missing: When all the markers are missing, the process model is used to reconstruct the markers position. From the position predicted by Extended Kalman filter and using the approximately constant distances between marker, the position of occluded markers are approximated.

V. RESULTS AND DISCUSSION

The tracking method was tried out on several different simulated datasets:

- **Case 1**: No occluded markers
- **Case 2**: One hidden marker for 50 frames
- **Case 3**: One hidden markers for 100 frames
- **Case 4**: All Three markers hidden for 150 frames
- **Case 5**: One hidden marker for 20 frames three times

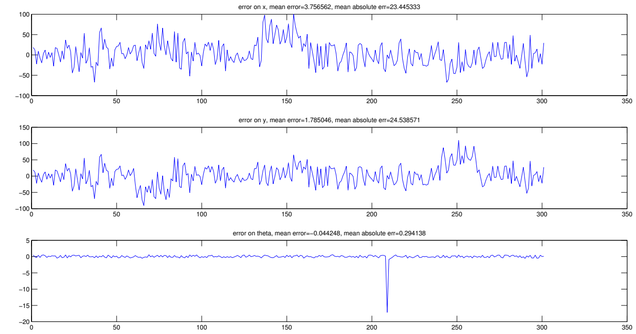
- **Case 6**: Two hidden markers for 20 frames three times
- **Case 7**: All three markers hidden for 20 frames three times

The position of the vehicle was tracked using our method and position of the vehicle was then compared with the true value. In table below represent returning position errors, the error were calculated in pixels due to the true data being represented in pixels as well.

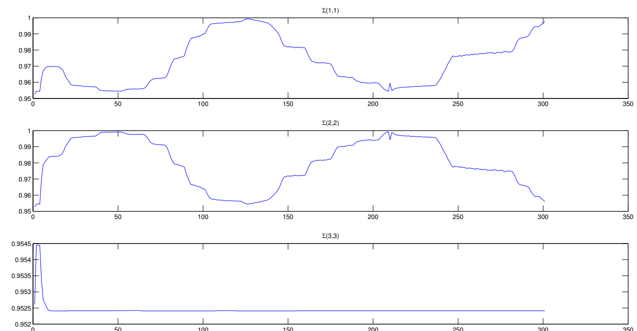
TABLE IV
RESULTS

Case	Mean Error	Absolute Error
1	(0.243, 0.341, -0.036)	(19.230, 19.426, 0.304)
2	(3.727, -8.718, -0.0450)	(21.376, 25.200, 0.294)
3	(16.027, -6.130, -0.045)	(28.800, 26.862, 0.293)
4	(24.858, 139.653, -0.0470)	(53.802, 154.168, 0.306)
5	(3.757, 1.785, -0.044)	(23.446, 24.539, 0.294)
6	(3.001, -0.511, -0.025)	(28.641, 31.833, 0.313)
7	(12.194, 13.051, -0.073)	(28.312, 30.605, 0.305)

Since it is hard to determine the relation of one pixel to a cm, since that depends on how close the tracking object is to the camera, number of cameras that can see the marker, calibration of the system and how well the cameras are linearized. Therefore, we can only reflect on the error, relative to the error generated when all the markers are seen. The error when all the markers are seen is shown in Case 1, the accuracy of estimation decreases with more markers being occluded. There is a large difference between case 2 and case 3, first when one marker is missing for a 50 frames interval and then one marker is missing for 100 frames interval. We can conclude that duration of occlusion has a big effect in decreasing the performance of our method. However occlusion for 100 frames means that the marker is missing for 10 seconds so a high error would be expected. Figure 3 shows a graphical illustration of the error on the position and covarience, when one marker is occluded. The marker was occluded between frames 60 - 80,135 - 155 and 240 - 260 resulting in larger error during those intervals. There also seems to be some correlation between the covariance error of x and y. (The large down spike which occurs on the θ is due to numerical error since the angle goes from 180 to 0 at that point).



(a) Error on the position



(b) Covariance error

Fig. 3.

In order to get a better realization on how our methods works we created a visual model of tracking which shows true position, estimated position and three markers. The visual model is represented in figure 4, in this case where one marker has been missing for around 20 frames, which is approximately 2 seconds.

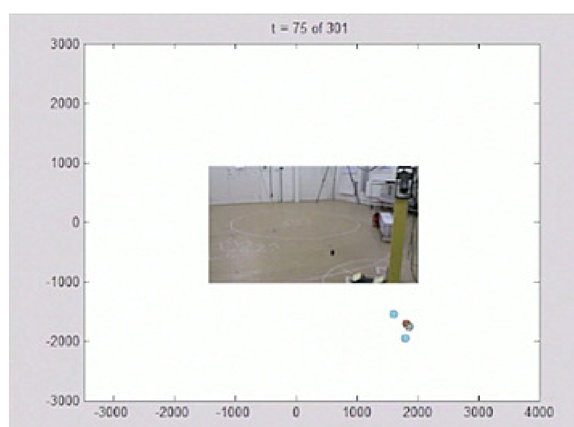
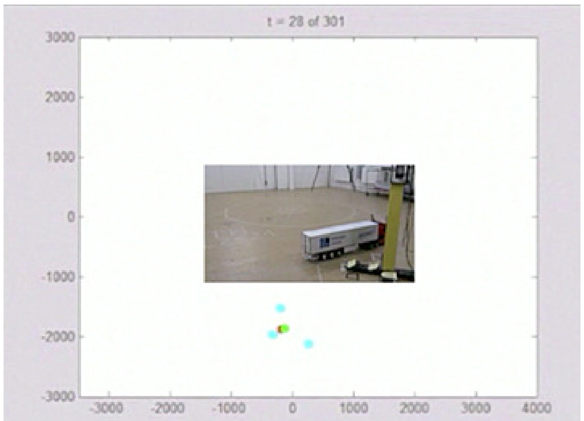
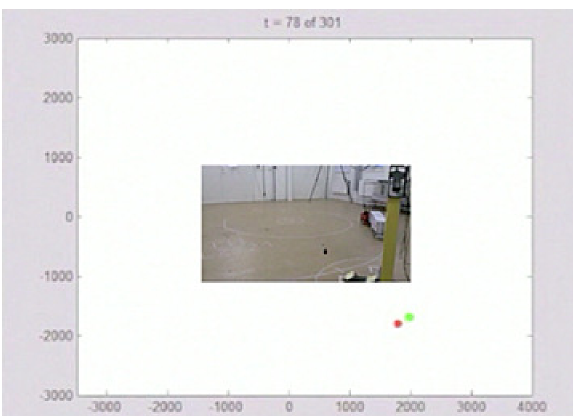


Fig. 4. One marker is missing

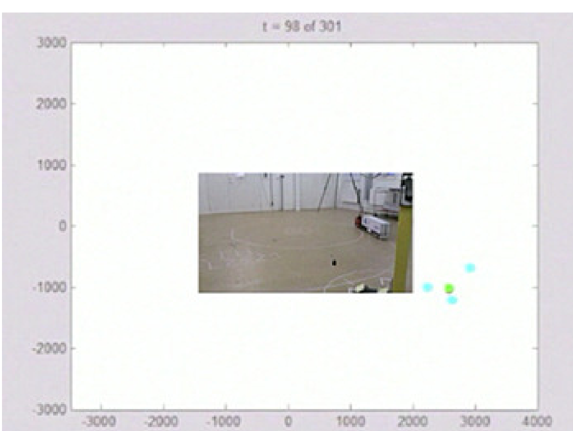
Here you can also see the vehicle driving on the circular path. From the image we can see that our estimated position is not far from the true position of the truck. Images below show the results when all three markers are occluded for approximately 20 frames and also what happens before and after the occlusion.



(a) Before the marker occlusion



(b) The markers has been missing for 20 frames



(c) After the marker occlusion

Fig. 5.

There is a noticeable difference between the those two cases when one markers is missing and when three markers are missing. When one marker is missing it position can be estimated using the information from neighbouring markers. In case of three missing markers the position of all the three markers is estimated from the process model. The process model was modeled so it can generalize and can generate good results on different types of motion. The process model is therefore not reliable alone to accurately estimate the position of the vehicle. Modeling the process for a certain type of motion will generate better result, we can assume. Before and after the three markers went missing the method seem to be generating good result on estimating the position of the vehicle.

VI. Conclusion

This paper addresses the problem of marker occlusion in motion capture system. It presents a method that can be used to track an autonomous vehicle in the presence of missing data. Approach used is based on extended Kalman filter and is updated using the information from neighbouring markers in order to estimate the position of non-visible marker or markers. This approach works efficiently with one or two markers being missing for a reasonable period of time. When three markers are missing for a short period of time the method gives good estimations as well. However, for estimations of all three markers for the longer period of time, a further work needs to be done. Future work will introduce a better process model and doing more work on model the noise of both systems. In the beginning of the project other prediction algorithm were considered such as Unscented Kalman filter, it is both efficient computationally wise and in handling the non-linearities and can be used with similar observation model. Other approach would be using extrapolation in case when all the markers are missing and taking into advantage the fixed marker distance when approximating missing marker or markers positions. Experiments of the method directly on the real data in real have not been carried out but our method is intended to be used in real-time.

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