A NOVEL FUSION ALGORITHM TO IMPROVE LOCALISATION ACCURACY OF AN INSTRUMENTED BICYCLE

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1. INTRODUCTION

Cycling is an increasingly popular mode of travel in cities due to the great advantages that it offers in terms of space consumption, health and environmental sustainability, and is therefore favoured and promoted by many city authorities. However, the relatively low perceived safety of cycling from the users' side currently presents itself as a hurdle towards higher uptake levels of cycling, and unfortunately, road accident statistics (1) confirm this perception as reality.

A typical collision pattern observed involves cyclists being "crushed" by turning motorised vehicles, due to their presence in the so-called "blind spot", which is to the left of the vehicle in the UK and to the right in countries with right-hand traffic (2). Up until a few years ago, the only options for tackling such a problem would be drawn from the domain of "hard" traffic engineering measures, (usually cost-intensive and/or severely disruptive, such as segregated lanes or vehicle type bans in certain streets). However, trends in the development of ubiquitous computing now offer smaller, more accurate and durable tools to support traffic safety interventions. Examples range from simple passive measures (3) to more advanced experimental active cyclist detection system (4).

But while such solutions certainly represent steps in the right direction in terms of preventing cyclist-vehicle collisions, they are limited in what they are unable to perform any reliable prediction of accidents due to their inability to accurately track the cyclist's trajectory and estimate his/her position in a critical time-horizon of 5-10 seconds. Indeed, the accurate (< 1 m) localisation of the cyclist is a necessity when it comes to preventing collisions, but so far remains an important unresolved challenge, as none of the existing mainstream technologies (GPS, WiFi etc.) can achieve it. Enhanced positioning systems, on the other hand, such as U-blox (5) and Spatial (6) Inertial Navigation System (INS), can achieve accurate positioning in theory, but they are specifically designed for four-wheel vehicles and are therefore very expensive when used for tracking bicycles. Besides, the dynamics of a bicycle is very complex and different from an ordinary vehicle, and so the accuracy of such enhanced positioning systems will differ greatly when used on a bicycle.

The research reported here focuses on the development and testing of an innovative technological solution for accurately localising and tracking cyclists in urban environments using a low-cost micro-electromechanical systems (MEMS) sensor configuration on a prototype instrumented bicycle system, called "iBike" (7). The ultimate goal is to develop a collision prediction and avoidance system, and the present paper presents a novel fusion technique that could be utilised to improve localisation accuracy based on Wireless Communication Technologies (WCT) widely found in cities as well as Global Navigation Satellite System (GNSS) positioning.

2. METHODOLOGY

2.1 Bicycle yaw angle Kalman filter

The yaw angle has been identified as an important parameter to compute the relative position. However, sensor data in the real world can be noisy, and in the case of a bicycle some of the kinematic parameters, such as the roll angle, cannot be determined accurately due to the physical structure of the vehicle. One way to improve the accuracy is to employ multiple sensors to measure the same parameter with alternative approaches. To apply this method successfully, the data from the multiple sensors must be fused with an appropriate technique. For this reason, the discrete Kalman filter described in (8) and (9) is studied. Subsequently, a linear time-varying state space model is developed, and the result is presented below.

$$\boldsymbol{X}_{[k]} = \begin{bmatrix} \psi_{[k]} \\ \omega_{bias[k]} \end{bmatrix} = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \psi_{[k-1]} \\ \omega_{bias[k-1]} \end{bmatrix} + \begin{bmatrix} \Delta t \\ 0 \end{bmatrix} \omega_{m[k-1]} + \boldsymbol{w}_{[k-1]} \tag{1a}$$

$$\boldsymbol{Z}_{[k-1]} = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}\psi_{[k-1]} \\ \omega_{bias[k-1]}\end{bmatrix} + \boldsymbol{v}_{[k-1]} \tag{1b}$$

where, $\boldsymbol{X}_{[k]}$ is the state vector at time k, ψ is the frame yaw angle, ω_m is the yaw rate, ω_{bias} is the bias which is incorporated in an electronic gyroscope, $\boldsymbol{w}_{[k]}$ is the Gaussian process noise with covariance matrix $\boldsymbol{R}_{[k]}$, $\boldsymbol{Z}_{[k]}$ is the vector of measurements and $\boldsymbol{v}_{[k]}$ is the Gaussian measurement noise with covariance matrix $\boldsymbol{Q}_{[k]}$.

The covariance matrices $\boldsymbol{Q}_{[k]}$ and $\boldsymbol{R}_{[k]}$ are assumed constant of the following form:

$$\boldsymbol{Q}_{[k]} = \begin{bmatrix}\sigma_{\omega}^2 & 0 \\ 0 & 0\end{bmatrix}, R_{[k]} = \sigma_{\psi}^2 \tag{2}$$

where the values σ_{ω}^2 and σ_{ψ}^2 can be approximated through field experiments using the well-known expression of variance of a random variable $\tilde{\alpha}$ from N observations:

$$\sigma_{\tilde{\alpha}}^2 = \frac{1}{(N-1)}\sum_{i=1}^{N}|\tilde{\alpha}_i - \mu_{\tilde{\alpha}}|^2 \tag{3a}$$

With

$$\mu_{\tilde{\alpha}} = \frac{1}{N}\sum_{i=1}^{N}\tilde{\alpha}_i \tag{3b}$$

2.2 Bicycle position Kalman filter

In previous work by the authors, a dead-reckoning (DR) algorithm was developed in order to estimate a bicycle's current position based upon a previously determined or known position (7). However, from the perspective of a fusion algorithm, the two-step DR procedure described in the earlier work is rather unsuitable, and therefore an alternative approximation positioning model is developed. The new model relies on the assumptions that the effective steering angle (β) of a bicycle never equals zero and that the arc distance d_r is very small compared to the turning radius R, such that it can be approximated as a straight-line. Thus, based on the geometry of Figure 1, the position of the rear frame between time t_{k-1} and t_k is approximated in body fixed coordinates by:

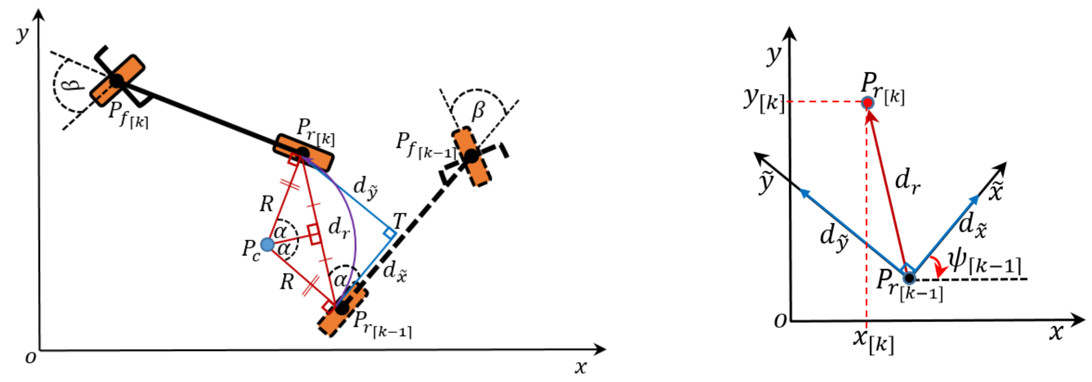
$$d\tilde{x} \approx d_r\, cos\left(\frac{\Delta\psi}{2}\right) \tag{4a}$$

$$d\tilde{y} \approx d_r\, sin\left(\frac{\Delta\psi}{2}\right) \tag{4b}$$

where $\Delta\psi$ is the instantaneous central angle (twice the angle α in Figure 1a)

Thus, the kinematics model for the position of the bicycle in the global coordinate system is then portrayed by:

$$\begin{bmatrix}x_{[k]} \\ y_{[k]}\end{bmatrix} = \begin{bmatrix}x_{[k-1]} \\ y_{[k-1]}\end{bmatrix} + \begin{bmatrix}cos(\psi_{[k-1]}) & -sin(\psi_{[k-1]}) \\ sin(\psi_{[k-1]}) & cos(\psi_{[k-1]})\end{bmatrix}\begin{bmatrix}d\tilde{x}_{[k-1]} \\ d\tilde{y}_{[k-1]}\end{bmatrix} \tag{5}$$



(a) (b)

FIGURE 1: (a) Bicycle geometric relationship with body and global coordinates system and (b) vectors translation into the global coordinates. In the diagrams above: x & y are the global coordinates frame, $\tilde{x}$ & $\tilde{y}$ are the body coordinates frame, o is the origin, R is the turning radius, ψ is the frame yaw angle reference to x-axis, δ is the steering angle, β is the effective steering angle, d_r is the travelled distance, α is the half of the central angle, P_c is the centre of a turning circle, P_r and P_f are the rear wheel and front wheel positions in the global frame respectively and the subscript k is associated with time.

The position Kalman filter is based on the DR algorithm derived through (4a), (4b) and (5). Assuming the global position coordinates $x_{[k]}$, $y_{[k]}$ as states, and also as outputs, and $d\tilde{x}_{[k]}$, $d\tilde{y}_{[k]}$ as inputs, equation (5) gives rise to the following position model.

$$\boldsymbol{X}_{[k]} = \begin{bmatrix} x_{[k]} \\ y_{[k]} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{[k-1]} \\ y_{[k-1]} \end{bmatrix} + \begin{bmatrix} cos(\psi_{[k-1]}) & -sin(\psi_{[k-1]}) \\ sin(\psi_{[k-1]}) & cos(\psi_{[k-1]}) \end{bmatrix} \begin{bmatrix} d\tilde{x}_{[k-1]} \\ d\tilde{y}_{[k-1]} \end{bmatrix} + \boldsymbol{w}_{[k-1]} \quad (6a)$$

$$\boldsymbol{Z}_{[k-1]} = \boldsymbol{X}_{[k-1]} + \boldsymbol{v}_{[k-1]} \quad (6b)$$

where ψ is the output yaw angle from the bicycle yaw angle Kalman filter described in the previous section.

Hence, the above model is utilised to derive the relevant parameters for the Kalman filter algorithm and the covariance matrices $\boldsymbol{Q}_{[k]}$ and $\boldsymbol{R}_{[k]}$ for the filter are assumed constant of the following form:

$$\boldsymbol{Q}_{[k]} = \begin{bmatrix} \sigma_{sys}^2 & 0 \\ 0 & \sigma_{sys}^2 \end{bmatrix} \quad (7a)$$

$$\boldsymbol{R}_{[k]} = \begin{bmatrix} \sigma_{pos}^2 & 0 \\ 0 & \sigma_{pos}^2 \end{bmatrix} \quad (7b)$$

The value of σ_{sys}^2 can be derived experimentally from the filtered yaw angle and distance measurements, while the value of σ_{pos}^2 can be approximated experimentally from a number of observations of absolute measurements for a known location.

3. FIELD EXPERIMENT AND RESULTS

Figure 2a illustrates the instrumented bicycle with the sensor configurations developed from the understanding of bicycle geometry and kinematics. In addition, a method was devised for establishing the ground truth of the experiment, against which the reconstructed trajectory from the presented sensor configuration would be validated. Specifically, a route was selected around City, University of London's campus and was then mapped using topographical surveying techniques. The survey was conducted prior to the actual experiment with the iBike, and the precise coordinates of a number of points were measured and recorded using the UK Ordnance Survey (Eastings and Northings) coordinate system (10).

(a)

(b)

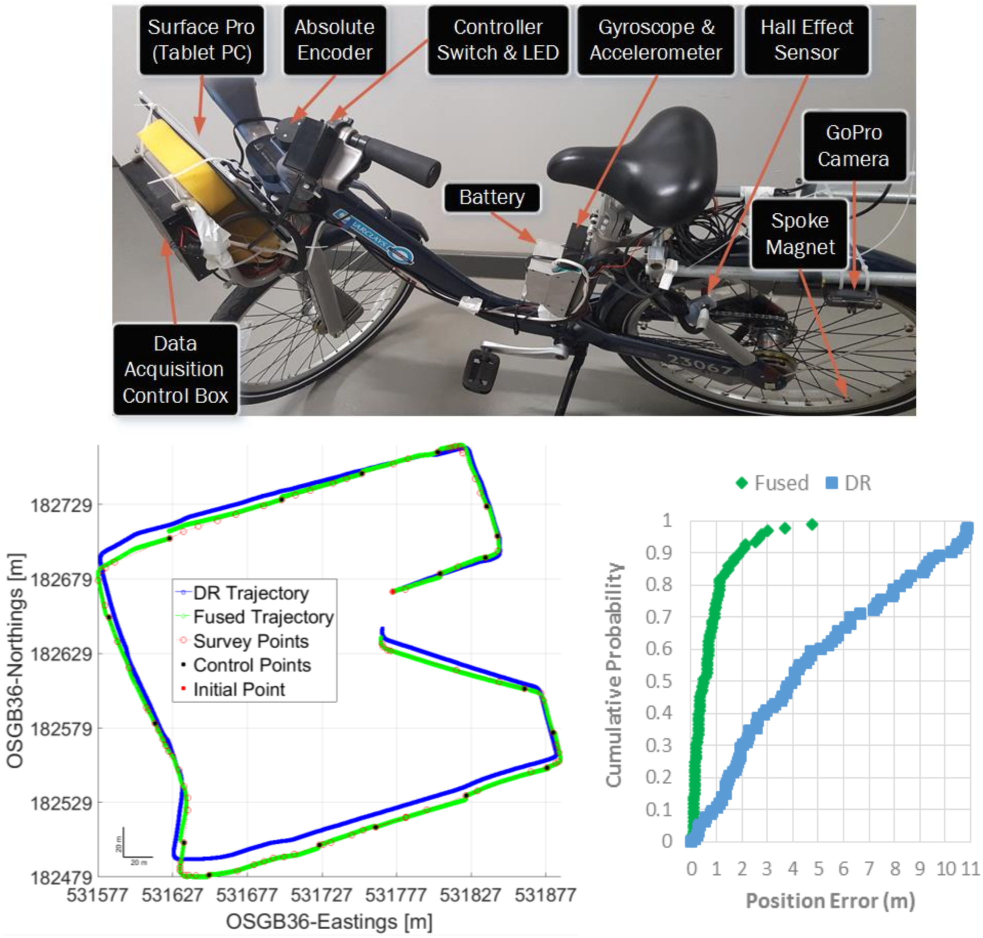


FIGURE 2: (a) The developed iBike system with the sensor configurations, (b) comparison of the trajectories (left) and cumulative error distributions (right).

During the actual experiment, the instrumented bicycle was ridden directly over (or as close as possible to) the surveyed points. As a result, approximate coordinates of the bicycle at the surveyed locations were available and this enabled to approximate the accuracy of the overall system with the proposed algorithms in Section 2. The overall survey route consisted of 93 points and had an approximate length of 1050 m from start to end.

The results obtained from a single journey along the surveyed route are illustrated in Figure 2b (left), where the blue line represents the reconstructed trajectory from the iBike sensor data and the DR model and the green line represents the fused trajectory based on the Kalman filters. The red hollow circles represent the survey points established prior to the experiment, while the black dots represent the control points used for the bicycle position Kalman filter in Section 2.2.

As can be seen from the graph, the reconstructed trajectory based on the iBike data with the DR technique alone is prone to drift; however, the fused trajectory, based on the Kalman filters and a random selection of control points from the survey, clearly indicates an improvement on the overall results. Consequently, this demonstrates that the novel sensor fusion algorithm developed in this study, certainly, improves the positioning accuracy and reliability. As a result, the overall methodology can be applied to accurately track cyclists and it can potentially be utilised with a collision warning algorithm to minimise the occurrence of false alerts.

Furthermore, to examine the accuracy of the overall methodology, a k-nearest neighbours algorithm, available through MATLAB's "knnsearch" function, was applied to the generated trajectories together the survey points. This process helped to extract the points which are correlated with the survey points and allowed to compute the error at each survey point for the DR and fused trajectories. Figure 2b (right) shows the cumulative distribution of the computed positional error.

4. CONCLUSIONS

In this paper, the kinematics and the turning geometry of a bicycle were studied to formulate a geometric relationship of the steering mechanism. Then a simplified model was developed for a dead-reckoning algorithm, enhanced through two sets of Kalman filter models to correct for the yaw angle and position errors over time in order to prevent drifting errors over long distances. The filters were then successfully applied to the collected field data from the iBike system and the known chosen coordinates from the survey path. The overall results of the field experiments show that it is possible to achieve a higher accuracy using the developed algorithms; in fact, with 70-80% probability, a position can be estimated with an accuracy of 1m or less. On the other hand, the DR error accumulates continuously, and it can be used to estimate a position with an accuracy of 1 m or less only with a 10% probability.

It should be additionally noted here that, due to practical reasons pertaining to the cyclist's vision and skill, as well as to the surrounding traffic conditions, the bike could often not be ridden exactly over the survey points. This meant that there was very likely an inherent error in the measurement relating purely to external factors rather than to the system itself. Thus, the actual positioning error could be even lower than what is reported in this study. However, since the ultimate aim is to utilise the developed methodologies in a safety-critical application, the error which falls above 1 m for the fused trajectory will be addressed in future work.

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