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Improving the Orientation Estimation in a Packet Loss-affected Wireless Sensor Network for Tracking Human Motion

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***Abstract* – This paper deals with a method to limit the consequences of packet loss on the accuracy of a real-time human motion tracking system based on Wireless Sensor Network (WSN). Since the need for a prolonged battery life is a prominent commitment in a WSN design, the power budget is so low that communication turns out to be not reliable enough for real-time requirements. Whereas packets getting lost may not represent a big deal in most of WSN applications, they are very likely to cause troubles in a system supposed to sample, stream and compute under very tight constraints. For this reason, countermeasures have to be taken in order to tolerate packet loss and limit its impact on the body segments' orientation estimation. The experimented method interpolates between quaternions produced by complementary algorithms merging smoothness of motion under ordinary circumstances with the capacity of fast recovery from loss. The results look promising and pave the way to further research for loss tolerance solution in low-power wireless systems.**

***Keywords*—** WSN, Motion tracking, Packet loss, Spherical Linear Interpolation

I. INTRODUCTION

In the recent years, engineering science has paid increasing attention in medical field, since technology has proved to be supportive in diagnosis and treatment. One of the most adopted techniques in observing the patient's answer to therapy in physical rehabilitation is motion tracking, which helps to identify and quantify dysfunction residue.

The system discussed in [1, 2, 3] offers the possibility to keep track of the patient's whole-body motion behavior in real time, relying on wireless sensor nodes, equipped with Inertial/Magnetic Units (IMUs), to wear on the body segments. IMUs sample and collect quantities to be off-board processed in order to find out the spatial orientation of the body segments that nodes are attached to. Wireless connection plays an important role in streaming the samples to the computation unit in charge of orientation processing as it makes sure that the subject under monitoring does not suffer from constrained mobility in their daily life activities.

In order to achieve battery life extension, being the leading commitment in designing a WSN, a node is generally equipped with a low-power radio transceiver implementing IEEE 802.15.4 communication. After all, extended battery life comes at a price: the less the power is used, the lower the communication reliability is, meaning that the probability of packet loss may reveal itself to be significant. In most of WSN applications, communication occurs once in a while and retransmission is a viable way to overcome losses. Unfortunately, the strict time constrains on sampling, processing and sending in real-time systems do not allow to broadcast once again a packet supposed to be not delivered. This is true anytime a processing task cannot be postponed due to the needs for immediate feedback to provide. For instance, augmented reality applications have to adapt their outputs according to the change of spatial position and orientation as it happens [4]. In those cases, the only action one can take to face loss is to deal with it: loss tolerance countermeasures must aim at the reduction of the relative effects on the system outputs.

Packet loss in real-time motion tracking applications basically results in a temporary decrease of the sampling rate, whose value is essential to capture a subject's movement adequately. In particular, for systems like that of [1, 2, 3], it can seriously harm the capability of the system to provide the user with accurate real-time measurements (e.g., an avatar in motion capture may happen to pose incorrectly). The problem is even bigger in applications with tens of nodes working in conjunction to trace the whole-body motion, wherein the overall probability of packet loss comes from the product of the single node probability by the node count.

This paper discusses and experiments with an interpolation method to reduce the effects of packet loss on the measurement accuracy of real-time motion tracking applications based on IMU. To this aim, the outputs of two different algorithms are merged looking for a good compromise between motion smoothness under ordinary circumstances and the capacity of fast recovery from loss.

The remainder of this work is organized as follows: Section II focuses on the effects of packet loss on the estimation by different classes of algorithms, Section III discusses the method adopted to limit the consequences of sample loss. Finally, Section IV reports the results, and Section V concludes the work.

II. PACKET-LOSS ON ORIENTATION ESTIMATION

The problem of tracking and reconstructing the subject's movements can be modeled as the problem of finding out the spatial orientations, at any given time, of each of the segments the body is composed of. This is made by determining the sensors' orientations, expressed as quaternions ${}^B_E\mathbf{q}$, processing triaxial measurements from gyroscope, accelerometer and magnetometer. Theoretically, two main approaches are possible in order to estimate an orientation: either integrating the angular rates or referring to the projections of the Earth's gravity and magnetic field onto the sensor frame. In the former case, estimation relies exclusively on gyroscope data, in the latter accelerometer and magnetometer measurements are used as the inputs. Integrating angular rates means keeping an internal state (stateful) relying on the history of gyroscope data, while one sample of acceleration and magnetic field suffices to find orientation (stateless). In practice, both approaches, when working separately, fail to come up with a result being fit to represent human motion accurately. Gyroscope data are affected by bias that changes unpredictably in time, leading to an integration error that drifts remarkably in few seconds. On the other hand, accelerometer and magnetometer data are basically noisy, and so are the resulting orientations, in addition to suffering from interference caused by external acceleration and magnetic perturbations.

These are the reasons why data-fusion algorithms are the best candidates to solve the Wahba's problem [5] and tackle the mentioned issues. They put together both approaches in order to cancel out each other's weaknesses. Several proposals have emerged over the years (e.g., those in [6, 7, 8]), all being based on the following property

$$ {}^B_E\dot{\mathbf{q}} = \frac{1}{2}\, {}^B_E\mathbf{q} \otimes {}^B\omega \tag{1} $$

where ${}^B\omega$ stands for the angular rates. The derivative quaternion is somehow multiplied by the sampling period Δt to obtain a part of the solution to be merged with that from accelerometer and magnetometer. Specific algorithm parameters (e.g., time constants in Kalman filters) influence the speed at which the computation converges to the solution.

Every time a packet gets lost a gap in the history of angular rates disrupts the integration, resulting in the gyroscope-related part of the solution not seeing the movement the subject has made meanwhile. The effects experienced by the virtual animation in this scenario are some of the body segments falling behind the actual movement, and in some cases awkward postures may show up. Fig. 1 exemplifies a possible effect of loss during an arm extension along the shoulder axis, when forearm and humerus of the monitored person move jointly aligned. During the arm extension performance, the difference between forearm and humerus pitch angles, determining the elbow joint angle, should be ideally constant to 0°, but a loss of a humerus mote's packet makes the relative orientation fall behind, resulting in elbow angle going up to not negligible values. In Fig. 1, such artificial joint angle is highlighted and an example of the elbow angle is reported.

Solutions based on instantaneous accelerometer and magnetometer data alone, known as single-frame algorithms (e.g., FQA [9], TRIAD [10] and QUEST [11]), feature more packet-loss resilience as they do not take a long convergence time and aim directly at the instantaneous solution.

Fig. 2 shows the ideal humerus pitch angle obtained when a loss occurs after 40 s, against the humerus pitch angles produced by single-frame algorithm (red line) and data-fusion algorithm (blue-line). As can be seen, ideal pitch angle grows linearly with time, while single-frame trajectory gets back on its track reacting to the same loss faster than what happens for data-fusion trajectory. That gives the idea of how big the toll is, in terms of jerky trajectories, to reduce the maximum deviation when samples get lost.

Fig. 3 shows the magnitude of the errors for the humerus pitch angles reconstructed by single-frame and data-fusion

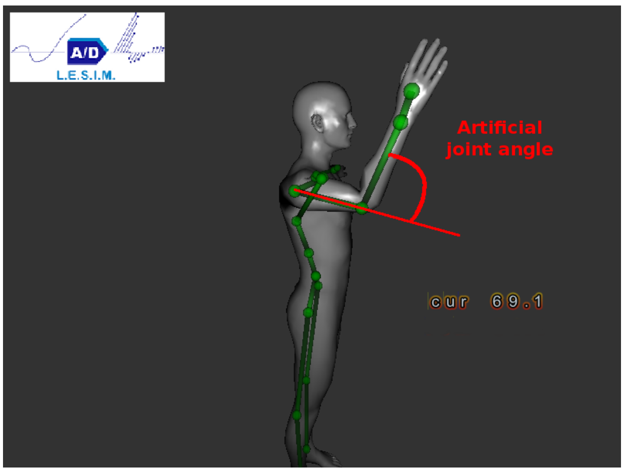

Fig. 1. Packet loss may cause to see joint angles deviating remarkably from real motion in data-fusion algorithms.

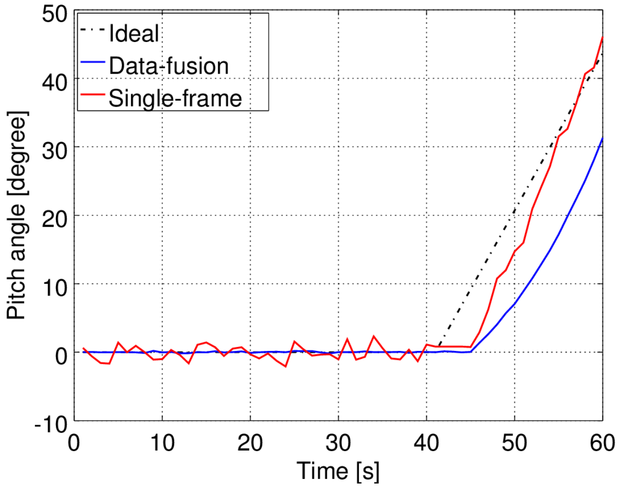

Fig. 2. Humerus pitch angle trajectories.

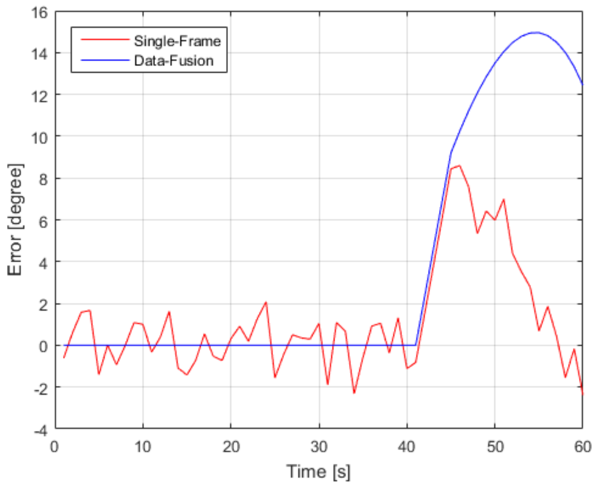

Fig. 3. Errors magnitude for both the reconstructed trajectories.

algorithms, with respect the the ideal one. The maximum error angle is $8.5°$ for single-frame algorithm and $14.9°$ for data-fusion algorithm.

III. A HYBRID APPROACH

In the light of what is said in Section II, it should be clear that the trade-off in picking single-frame or data-fusion algorithm is between the orientation accuracy under normal conditions and loss resilience.

In order to strike the balance, the idea behind the method that this paper deals with, is based on interpolation of quaternions computed by two algorithms, as depicted in Fig. 4. This approach promises to be more solid than raw data interpolation as the latter requires to make assumptions on the type of tracked motion, which is unfortunately unpredictable in general cases. Having two unit quaternions representing rotations, an in-between rotation can be found by interpolating them. Linear interpolation is not the best solution since a rotating joint is expected to move along a smooth curve. *Spherical Linear IntERPolation* (*SLERP*) is defined as a linear interpolation performed on the surface of a unit sphere, used in the field of computer graphics to obtain smooth motion. Analytically, let $\mathbf{q}_A$ and $\mathbf{q}_B$ be two unit quaternions, Ω be the rotation angle, and $\mu \in [0,1]$ be a real scalar value, *SLERP* resulting from

$$\begin{aligned} \mathbf{q}_C &= SLERP(\mathbf{q}_A, \mathbf{q}_B, \mu) = \\ &= \frac{\sin(1-\mu)\Omega}{\sin\Omega}\mathbf{q}_A + \frac{\sin\mu\Omega}{\sin\Omega}\mathbf{q}_B \end{aligned} \tag{2}$$

carries out a spherical interpolation between $\mathbf{q}_A$ and $\mathbf{q}_B$ by an amount μ, with $\mathbf{q}_C$ determined as a point along the circle arc on the surface of the unit sphere (Fig. 5).

The method uses *SLERP* to reduce the convergence time taken by the data-fusion algorithm right after a loss, interpolating by μ depending on the number of samples lost consecutively λ. As λ increases, estimation ${}^B_E\mathbf{q}_d$ from data-fusion loses reliability, therefore the interpolation should tend towards the single-frame solution ${}^B_E\mathbf{q}_s$ since ${}^B_E\mathbf{q}_d$ is likely to have missed most of the recent motion. On the other hand, as long as λ stays moderate, ${}^B_E\mathbf{q}_d$ should be preferable as it guarantees smoothness. For this reason, the interpolation parameter μ_λ is defined as

$$\mu_\lambda = \frac{\rho}{\frac{\lambda}{\tau} + \rho} \in (0,1]\,, \qquad \rho, \tau \in \mathbb{N}_+ \tag{3}$$

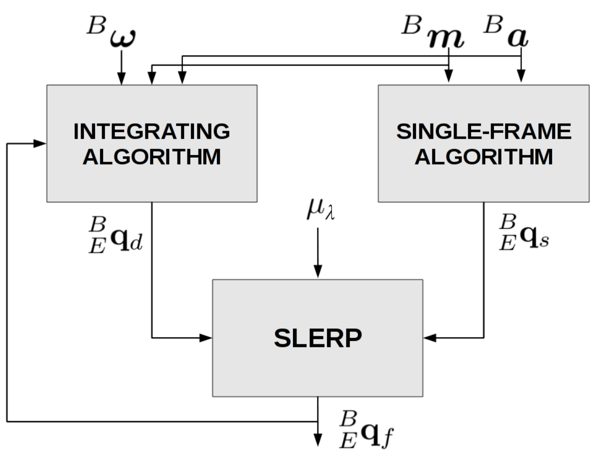

Fig. 4. Interpolation between data-fusion and single-frame quaternions.

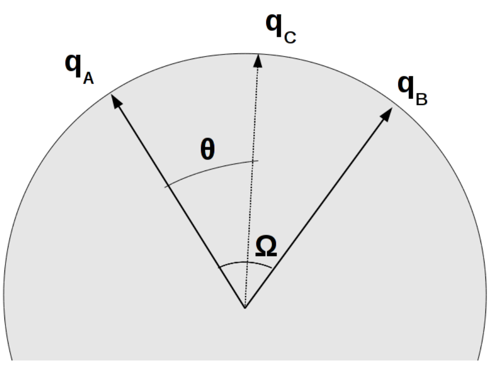

Fig. 5. Spherical linear interpolation.

with

$$ {}^B_E\mathbf{q}_f = SLERP({}^B_E\mathbf{q}_s,\ {}^B_E\mathbf{q}_d, \mu_\lambda) \quad (4) $$

Combining equations (2), (3) and (4) results in

$$ {}^B_E\mathbf{q}_f = \frac{\sin(1-\frac{\rho}{\frac{\lambda}{\tau}+\rho})\Omega}{\sin\Omega}\ {}^B_E\mathbf{q}_s + \frac{\sin\frac{\rho\Omega}{\frac{\lambda}{\tau}+\rho}}{\sin\Omega}\ {}^B_E\mathbf{q}_d \quad (5) $$

which describes the interpolated quaternion as a function of the lost samples.

IV. EXPERIMENTAL RESULTS

The case study for the early experiments relies on [10] for the single-frame algorithm responsible for ${}^B_E\mathbf{q}_s$ and on [7] for the data-fusion part ${}^B_E\mathbf{q}_d$, which performed fine in motion-tracking trials [12].

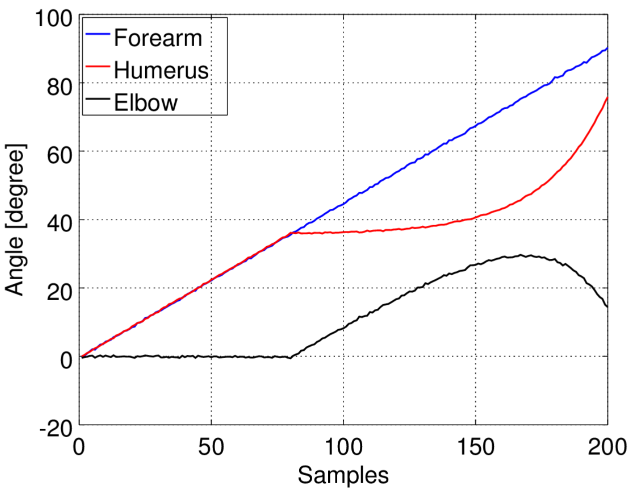

Fig. 6. Trajectories produced by data-fusion deviate remarkably from real motion due to loss.

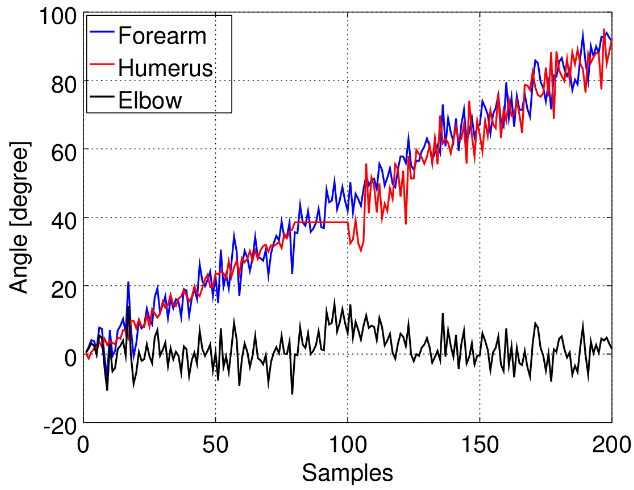

Fig. 7. Single-frame algorithm produces jerky trajectories.

The sensor platform used in experiments consists of a 9-degree-of-freedom IMU packing an ST-L3GD20 digital gyroscope with 16 bits and an ST-LSM303DLHC chip including a 12-bit accelerometer and a 16-bit magnetometer sampling at 50 Hz. The raw data have been organized in 6-sample packets, collected by a personal computer from a sensor via wired serial communication in order to get continuous lossless sequences of samples. These sequences then have been artificially injected with several profiles of loss, so as to create artificial lossy sample sequences and analyze the algorithm performance under different conditions of network reliability. Such packet-loss profiles have been selected according to previous experiments carried out at a preliminary stage of this study. In order to assess effects not only on the single node orientation, but also on joint angle measurement, sequences from two adjacent nodes have been acquired. In particular, raw data related to a 90° arm extension have been acquired and the pitch angles of humerus and forearm have been analyzed. The raw data sequence of the humerus trajectory has been injected with a loss λ of four packets right after 80 samples.

Fig. 6 reports the performance of the data-fusion algorithm. It can be seen that the occurrence of packets loss results in humerus pitch angle (red line) different from forearm one (blue line). As reported in Section II, this results in elbow angle (black line) goes up to increasing values. Moreover, the slow convergence rate causes a considerable deviation of the elbow joint angle for more than 2 s (about 100 samples), which is not desirable in human motion capture. The noisy single-frame orientations issued by [10] are shown in Fig. 7 to reduce the upper-bound of elbow joint error below 20°, even though they return trajectories being unacceptably jerky. The performance of the interpolation method is

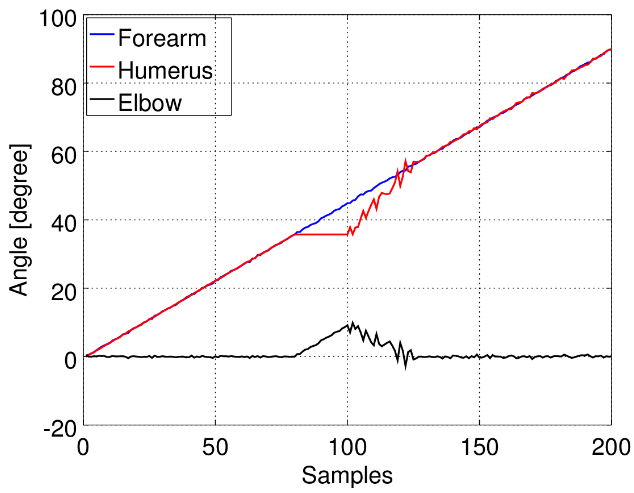

Fig. 8. Interpolation algorithm preserves the smoothness and limits the maximum deviation.

shown in Fig. 8, wherein the error of elbow joint angle stays valuable around 10° for about 1 s only. It is worth remarking that these early results seem to live up to the expectations, confirming that quaternion interpolation is a viable way to make the algorithms' advantages meet.

V. DISCUSSION

This paper presented an interpolation-based method to make the internal state of data-fusion algorithm recover fast after sample a loss, which is an event likely to happen in low-power WSNs because of packets not delivered. In doing so, the experimented approach interpolates a quaternion from the data-fusion algorithm with that computed by a single-frame algorithm, supposed to be fast in getting back in the neighborhood of the solution, yet still jerky. The results appear encouraging and suggest that harms from loss can be considerably reduced if complementary techniques are used.

It is worth pointing out that alternatives to quaternion interpolation exist to solve the problem. One could rely exclusively on a single-frame algorithm, prefiltering accelerometer and magnetometer data to reduce the impact of external disturbances. Unfortunately, filters often reduce also the motion dynamics that the system can capture.

Integrating algorithms can still be used, provided that some tweaks are put in place. The sampling rate Δt can be set according to the sample loss λ. The actual sampling rate could be temporary increased to $(1 + \lambda)\Delta t$ so that the first angular rates to be delivered after the loss would be handled as gyroscope data sampled over an extended period. This basically equals assuming that the node has moved at constant speed during the loss, although the uniform motion assumption is very likely to fail in free-to-move applications like that under analysis.

In alternative, raw data can be subjected to interpolation themselves, instead of quaternions. For instance, linear interpolation of gyroscope measures, which assumes that angular accelerations remain nearly constant, may turn out adequate as long as the motion stays smooth.

As previously said, convergence rate in data-fusion processing is impacted by algorithm-specific parameters: it is the case of the step size β that regulates the weight of accelerometer and magnetometer in [7], and of the covariance matrix P in Kalman filters. Adjusting these parameters in accordance with λ may help to increase the loss resilience of a system.

Future work will delve into raw data interpolation and comparing to quaternion interpolation. Also, adaptive covariance matrices in Kalman filters will be under the focus of further research.

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