CHAPTER

8 Data fusion for orientation sensing in wireless body area sensor networks using smart phones

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1 INTRODUCTION

Advancements in Information and Communication Technologies (ICT) has been revolutionary globally. In every aspect and field of life, things are changing; humans are seeking excellence day after day. The ICT outlined in this chapter is that involved in Smart Grids (the future of grids), in medical and bioinformatics, in computer science and many more. Sensor networks have proven their importance in almost every field of life. The Consideration of the potential of tiny nodes with little processing power, sensing and transmitting units has given birth to numerous sub domains in wireless personal area networks (WPANs). One of the most studied and useful domains is the Wireless Body Area Sensor Network (WBASN). These networks are mainly studied and applied as e-Health solutions. Considering healthcare, we can say that healthcare systems are in a transitional phase. Manual healthcare is being replaced by automated healthcare. It is transforming from centralized systems to distributed systems. If we fail to shift from centralization to distributed environments, our existing hospitals will be overwhelmed by the increasing population.

Besides there is more general awareness regarding healthcare. Now individuals are interested in observing their own physiology. Not only are sportsmen careful to monitor their health and fitness but also this type of technology can help in the prevention or control of diseases for individual from any background and with any medical history. Hence we can say that the coming era a shift from the hospital centric cure to the patient centric cure.

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2 WBASN AND E-HEALTH SYSTEMS

Considering present day era, we have reached a point where wireless communication is booming with numerous kinds of networks for numerous applications. There is a feeling that nothing we propose is outside the scope of the natural environment. One of emerging domains, ie, Body Area Network (BAN), has existed as long as any living being. We each have eyes that act as cameras seeing the environment, a nose that senses smell, a tongue that sense tastes and many sensors with in our skin that allow us to feel. All these sensors are connected to a hub known (the brain) and they send request/information and take orders. On sensing a smell, the sensor (nose) transmits a signal via a neuron to the brain and the brain gives orders regarding that specific environment. A variation on this concept is utilized in WBASNs. Sensors are deployed in/on a body through the underlying topology and they communicate with a central hub to give information/requests and take orders accordingly as depicted in Fig. 1.

Natural BANs are so perfect that there is no chance of collision amongst the various signals, and there is no energy issue, there is no malfunctioning in network behavior, until some unexpected event occurs. In comparison, the man-made BANs, on which researchers are working for the betterment of mankind, have countless issues. These cannot be as perfect as a natural BAN, though such artificial networks may help humans whose natural BAN is disturbed. A camera can be integrated that

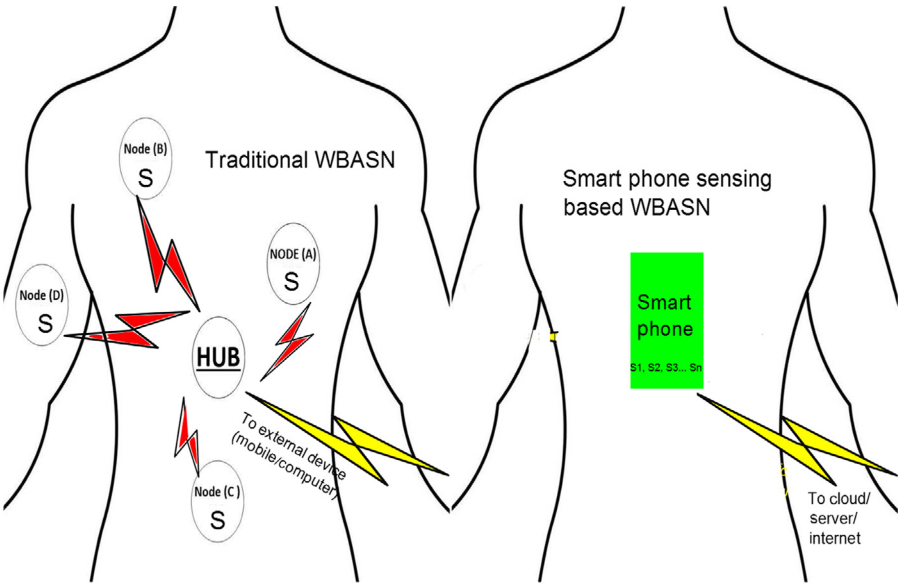

FIG. 1

WBASN for E-Health solutions.

may inform the brain regarding the environment it sees, or an ECG sensor may keep the doctor of a certain patient well informed regarding his heart condition. Besides medical issues, in today's digital era, why not exchange our digital profiles with each other by shaking hands or spend our leisure time playing motion games on a big screen and so on. We can use such networks for understanding the behavior of a targeted population regarding some predetermined subject. The application arena for a BAN is as wide as one can imagine. For any need applications sensor nodes need to be deployed on/in the body or in the vicinity of the body.

The sensor nodes generate sensed data and these data are used to investigate whatever it is intended to. At this point WBASNs present researchers with a challenge regarding the precise analysis and evaluation of data. The amount of data being sensed and transmitted continuously from the different sensors is enormous. Moreover, analyzing raw data can also be troublesome. The answer to these challenges is the Data Fusion Algorithm (DFA).

The concept of data fusion is not new. It is basically the procedure of gathering the data acquired from different sources and merging it to reveal a complete picture of an environment or state or any point of interest. If there is a large amount of information coming from different sources, using DFAs is a must for maintaining the quality and integrity of the data on which certain decisions are to be made. There are many algorithms and techniques for efficient data fusion (Majumder et al., 2001; Bar-Shalom and Li, 1995; Bar-Shalom et al., 1990; Raol, 2009; Zou and Sun, 2013; Cho et al., 2013). However, considering WBASNs, there are certain limitations; mainly with respect to power and computational constraints. The data fusion technique that has high computational cost with precision may not be applicable in certain scenarios where we have low computational power, and vice versa. These kinds of questions make researchers ponder not only on existing DFAs but also on the possibility of modifying or developing new algorithms for WBASNs.

2.1 DATA AGGREGATION AND DATA FUSION

In any sensor network, the amount of data generated for the sensed attribute/s of any sensor is enormous. Moreover, it is prone to corruption, as there might be interference. For example, interference due to pressure, temperature, EM waves, etc. This curried data cannot yield good results; in fact in WBASNs this can lead to disastrous decisions. Data Fusion is the answer to such failures or inaccuracies in the sensor readings. In the literature fusion is combined with many terms. We can find multiple terminologies that include fusion of data, ie, information fusion, data fusion, sensor fusion, data aggregation and sensor integration. All of these terms have been explicitly defined by their users and there is as yet no unified approach. Sensor Fusion normally relates with the fusion of data that sensors generate whereas, Information and data fusion are accepted as general terms with the same meaning (Abdelgawad and Bayoumi, 2012).

Joint Directors of Laboratories (JDL) (White, 1991) defines data fusion as "*multilevel, multifaceted process handling the automatic detection, association,* *correlation, estimation, and combination of data and information from several sources.*" Jayasimha (1994) states that data fusion is the "*Combination of data from multiple sensors to accomplish improved accuracy and more specific inferences that could be achieved by the use of single sensor alone*". In the same manner, multisensory fusion deals with the fusion of sensed data by different sensors and the orchestration of the data into one presentable format. Hence we can state that data fusion is the process of finding true values or reaching a correct decision by resolving conflicting sensed values via multiple sources.

Besides data fusion, there is another term that is widely used in the literature, data aggregation, mainly in the domain of Wireless Sensor Networks (WSN). Data aggregation refers to refining the voluminous raw data collected by a sensor. Simply stated, it is the summarization of the entire data. Fig. 2 illustrates the concept of multisensory data fusion, sensor data fusion, and sensor data aggregation. Data aggregation reduces the data and cannot be done for the applications where precision

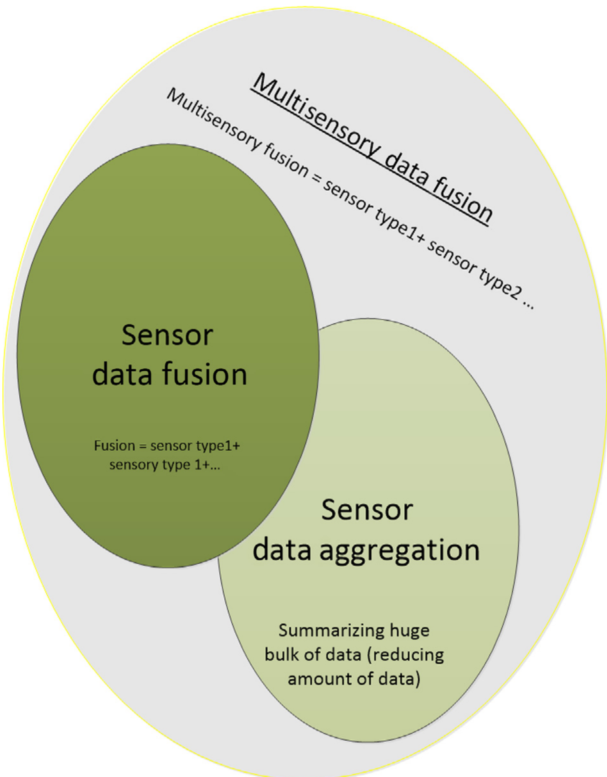

FIG. 2

Relationship amongst data aggregation and data fusion.

is demanded. Data aggregation may reduce the amount of data, but this may result in the elimination of an important set of data.

2.1.1 Data fusion algorithms

Data fusion is an important aspect in Computational Intelligence (CI). This results in making precise and accurate decisions. There is a huge application arena for DFAs. Anywhere we have to deal with data, or a large amount of data, and anywhere we need precision and data manipulation in a desired manner, DFAs provide the solution.

As shown in Fig. 3, DFAs can be grouped into four classes, ie, Inference, Estimation, Feature Maps and Reliable Abstract Sensing (Nakamura et al., 2007).

Inference algorithms are used when decisions rely upon the knowledge of perceived circumstances or situations or events. Inference means transition from one true state to another while the result is dependent on the previous result. Classical Inference algorithms are Baysian Inference (Box and Tiao, 2011), Dempster-Shafer Belief Accumulation Theory (Gordon and Shortliffe, 1984). Besides fuzzy logic (McNeill and Thro, 2014), Artificial Neural Networks (Mäkisara et al., 2014) and abductive reasoning (Walton, 2014) are major inference algorithms.

Feature Maps Algorithms intend to solve such problems where raw sensory data are not appropriate for use. Instead, certain features are selected amongst a whole set of sensed data. Normally Inference methods are used to extract a feature map.

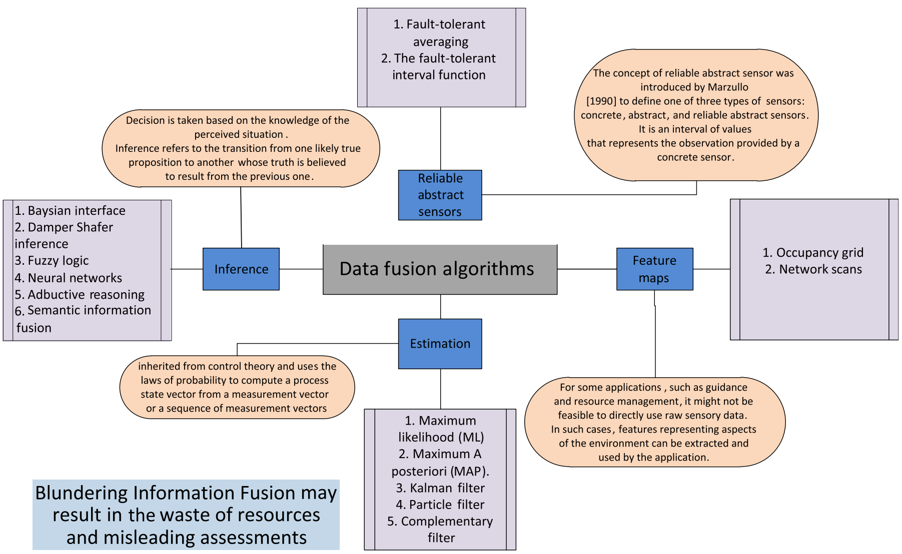

FIG. 3

Data fusion algorithms.

Occupancy Grid (Thrun, 2003) and Network Scans (Zhao et al., 2002) are two methods that lie in this class of algorithms.

Reliable abstract sensor methods are used in the context of time synchronization by maintaining lower and upper time boundaries (Marzullo, 1990). Fault Tolerant Averaging (Jayasimha, 1994) and Fault Tolerant Interval Function belong to Reliable Abstract Sensing group.

Estimation Algorithms are based upon control theory and are widely studied in different domains. The most prominent methods of this class are Maximum Likelihood (Kubo, 1992), Least Squares (Marquardt, 1963), Moving Average Filters (Sato, 2001), Kalman Filters (Srinivasan, 2015), Complementary Filters (Cockcroft et al., 2014), and Particle Filters (Gordon et al., 2004).

2.2 SMART PHONES FOR e-HEALTH MONITORING

The technology shift from mobile phones to smart phones is perhaps the fastest technology shift globally. Smart phones are penetrated deep into every ones lives. They have much more to offer than mobile phones. Today they have powerful processors, large memory, many built in sensors, along with multiple network interfaces. Discussing cellular technology, GSM is replaced with 3G and 4G networks offering high bandwidth that makes numerous applications feasible.

Confining ourselves only to sensory part, we can find accelerometers, gyroscopes, magnetometers, cameras, temperature sensors, GPS, microphones, ECG sensors, etc., in smart phones. This provides us with the opportunity to use these sensors in spite of the fact that they are expensive and complex sensory units. With regard to smart phones, different systems are developed for different applications. Considering e-Health solutions, Table 1 illustrates a few established systems (Want, 2014).

Table 1 Smart Phones for e-Health Solutions

Solution	Sensor Types	Application
SPA	Biomedical sensor, GPS	Heathcare suggestions
UbiFit Garden	3D Accelerometer	UbiFit Garden's Interactive Application
Balance	Accelerometer, GPS	Balancing
CONSORTS-S	Wireless Sensor, MESI RF-ECG	Healthcare Services

Keeping motion capture or physical activity monitoring in view, sensors such as accelerometers and gyroscopes are in use for different healthcare and assisted-living applications. With advent of smart phones that have accelerometers and gyroscope sensors research into their use for the said purpose has taken spotlight.

In this chapter, two sensor data fusion techniques (Kalman and Complementary) are analysed in context with WBASF anticipating WBASNs using smart phones. Simulations are conducted for comparison of these two estimation-based DFAs using comparative analysis. According to our results, considering human body movements, the Complimentary Data Fusion Algorithm (CDFA) is more appealing in comparison to the Kalman Data Fusion Algorithm (KDFA) due to its simplicity, and accuracy.

3 ORIENTATION SENSING

In WBASNs, activity monitoring and fall detection for the elderly is becoming a hot topic. Initially, we required a stationary-camera-based complex setup with very limited freedom of movement. This was replaced with Inertial Measurement Units (IMUs) for their improved mobility, wearability and ease of use (Bachmann et al., 2001; Zheng et al., 2005). These IMUs are now being replaced with smart phones that have built-in orientation sensors (Gyroscopes and Accelerometers). Moreover, they have high computational power and efficient transmitting modules making it more interesting for WBASF (Lane et al., 2010). The orientation sensors can track or monitor the activities of a human body precisely in accordance with its application and transmit the details directly to a programmed location.

As stated earlier, smart phones contain accelerometers and gyroscopes that can be related with motion capture systems in the form of IMUs. Pascu et al. (2012) proposed a medical application using smart phones for ambient health monitoring. The question of whether smart phones can take the place of IMUs is solved by Pascu et al. (2013). A motion capture facility if derived using kinematic models and displayed interpretable data on smart phone's screen. They used Kalman filtering for the data fusion of gyroscope, accelerometer and magnetometer sensory data. Besides Kalman filtering, Bayesian filtering, Central Limit Theorem and Dempster-Shafer are prominent.

3.1 SENSOR DATA FUSION: A LAYERED APPROACH

For Sensor data fusion, we have to iterate the whole procedure into three major steps as in Khaleghi et al. (2013) and illustrated in Fig. 4.

- Sensing phase: in which raw data is sensed by the sensor.
- Analysis phase: where decisions are to be made from sensed data.
- Dissemination phase: accurate information is handed over to user application.

At initial phase, ie, sensing phase, sensed data are processed to acquire different features, ie, mean, variance, min, max, etc. These features are submitted to the analysis phase. In the analysis phase, the required features are selected and fused

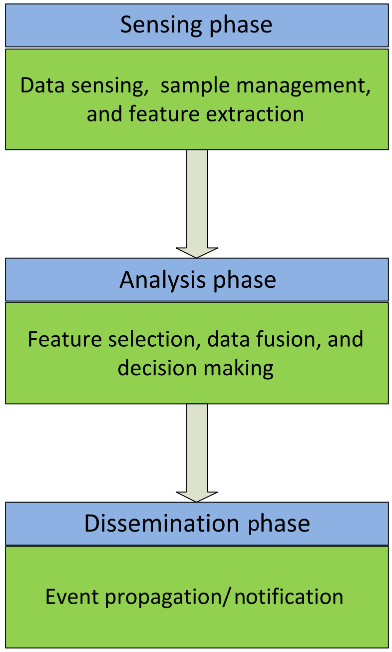

FIG. 4

Data fusion layers.

together to make a decision. That decision is fed to the dissemination phase from where this event is displayed on application modules.

To understand orientation sensing, we have to understand the basic functionality of the different sensors. The accelerometer and gyroscope are the most prominent ones besides magnetometer and inclinometer.

Accelerometers are meant to calculate G-force amongst the X, Y, and Z axes of any body. This sensor inevitably does not always work on the definition of acceleration as, *rate of change of velocity*. For simple motion-based sensing, these sensors are best to use. G-force embraces acceleration owing to gravity. If the sensor is placed facing up wards, the Z-axis reading of the accelerometer will be -1. Fig. 5 briefly describes calculations of an accelerometer.

Gyroscopes are meant to calculate angular velocities amongst X, Y, and Z axes. This sensor has no concern for orientation but takes care of rotation at different velocities. To accurately measure the orientation of a body, gyroscope and accelerometers have to consult each other to determine whether body is moving and in which direction. Fig. 5 explains the angular rotations that a gyroscope measures.

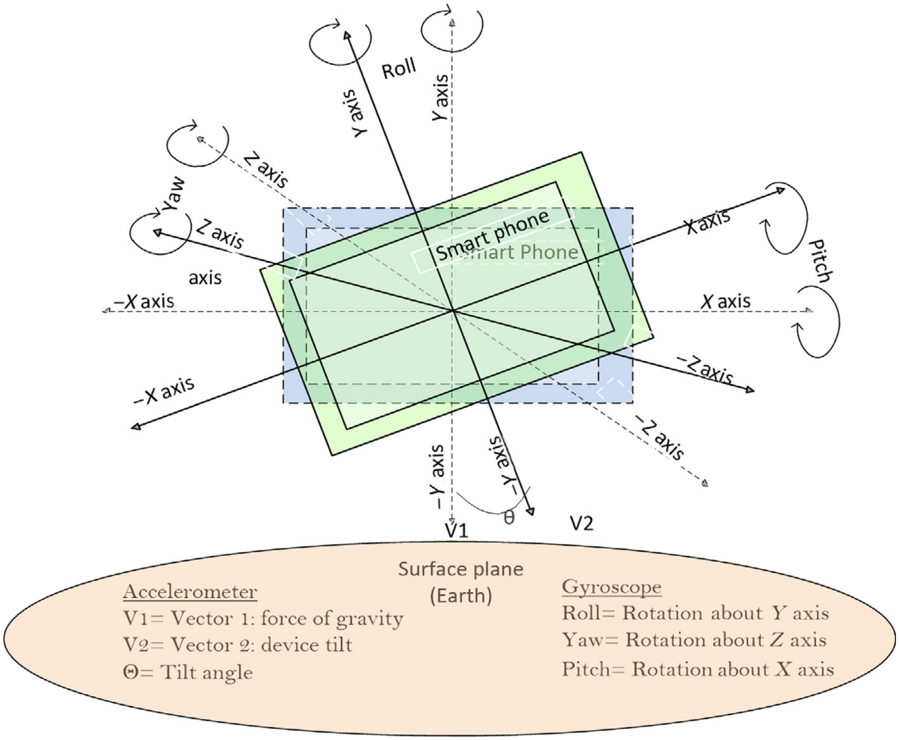

FIG. 5

Gyroscope accelerometer functioning.

The orientation of a body can be calculated with information gathered from the attached accelerometers and gyroscope articulated via quaternion and a rotation matrix to offer a precise calculation of the body's placement with respect to global coordinates.

4 ORIENTATION APPROXIMATION

The major objective of orientation approximation is to guess the rotation in relation to a coordinate frame of sensor and the rest of the world as precisely as possible. Three-dimensional IMUs typically use gyroscopes and accelerometers to measure the acceleration vector and rotational vector in a coordinate frame relative to global coordinates. Orientation approximation is conducted by fusing the above-mentioned vectors.

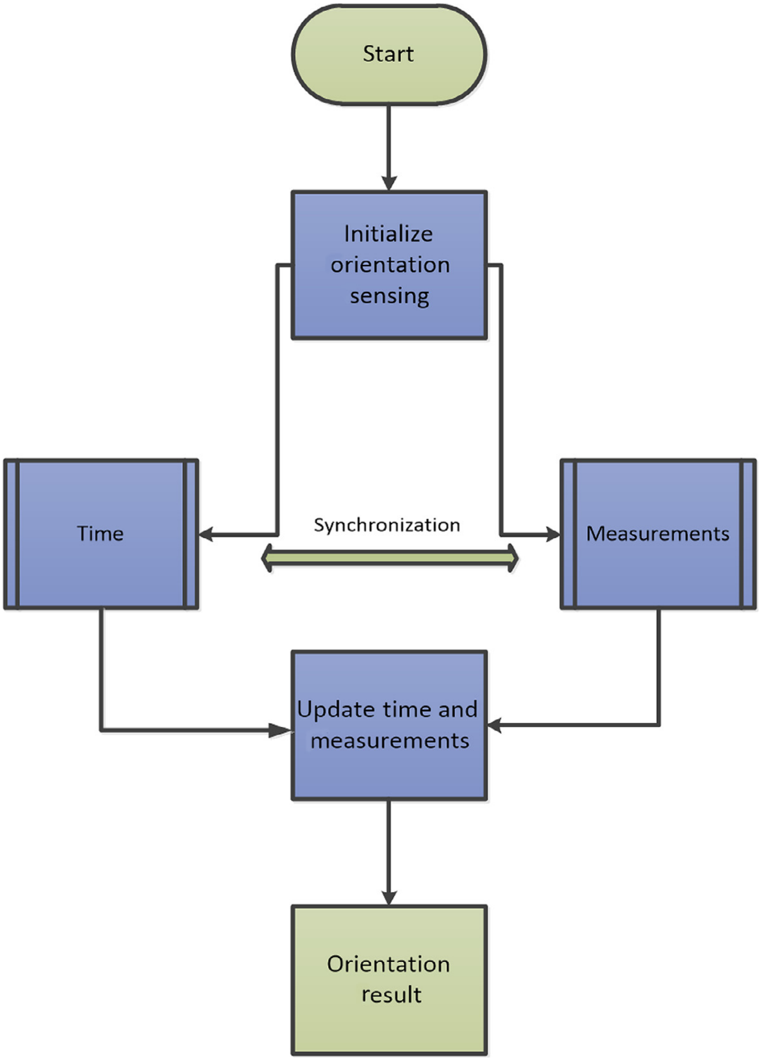

FIG. 6

Generalized orientation approximation algorithm.

4.1 GYROSCOPE ACCELEROMETER INTEGRATION

Gyroscope integration provides an approximation regarding relative rotation given that the initial rotation is known. This angular velocity, calculated by gyroscopes, is also directly integrated to deliver an accurate approximation even if the body is moving at high speed. A generalized orientation approximation algorithm is illustrated in Fig. 6. Authors in [32] presents gyroscope integration as in Eq. (1).

$$f_t = f_{t-1} + \frac{1}{2dt}(0, \vec{\omega}) \otimes \hat{f}_{t-1} \tag{1}$$

where

f_t = approximated orientation
dt = sample period
$\vec{\omega}$ = angular rate vector calculated in rad/s
$\otimes$ = quaternion multiplication operator.

Whenever any change in orientation occurs, approximated quaternion must also be normalized to omit or reduce angular errors that may persist. This integration presents two significant problems, ie,

- Any error in angular rate vector will increase cumulatively.
- Knowledge of the initial orientation of the body is a must to relate this to changes in positioning.

Vectors illustrate an approximation of the orientation that is related to the global coordinate frame. Combining these vectors and then comparing the result with the vectors for the initial position can provide us with details of the rotation that has occurred. Mathematically, this rotation "R" can be calculated as in Eq. (2).

$$R = \frac{v_i}{\vec{\omega}_i} \forall i \varepsilon (1, \ldots, n) \tag{2}$$

where

R = rotation
V_i = number of sensed vectors
$\vec{\omega}_i$ = reference vectors in global coordinates.

As depicted by Khaleghi et al. (2013) the qualms in sensory data rests not only due to inaccuracy and integration of noise in the sensed data, but wrong interpretations and inconsistencies also contribute in uncertainties regarding sensory data. The general algorithm used for orientation is defined as in Eqs. (3) and (4):

$$\vec{e} = \frac{\vec{a}}{||\vec{a}||} \tag{3}$$

$$R = [\vec{e}]^T \equiv \hat{f} \tag{4}$$

where $\vec{a}$ = acceleration vector.

Using vectors for approximation of orientation gives absolute values. On the other hand, if we discuss the accelerometer, it is polluted with noise due to the acceleration and gravity phenomenon that occurs in a moving body. Here we will discuss two of the most widely used DFAs, ie, Complementary filtering and Kalman filtering simultaneously.

4.2 COMPLEMENTARY FILTERING

CDFA is meant to derive one single output by combining two different measurements with different noise properties. Focussing on one case, accelerometer signal produces high frequency noise while the gyroscope results contain low frequency noise. These data fusion techniques apply both low and high pass filters as expressed in Eq. (5):

$$H_s = H_{LP(s)} + H_{HP(s)} = 1 \tag{5}$$

Using this approach of data fusion, we overcome the delay problem. Mathematically we can express CDFA equations as in Eqs. (6) and (7):

$$f_t = f_t + \frac{1}{k} f' \tag{6}$$

$$\hat{f}_t = \begin{cases} f_t' + \frac{1}{k}(f_t'' - f_t') & \text{for } |\|a\| - 1| < a_T \\ f_t' & \text{for} |\|a\| - 1| \geq a_T \end{cases} \tag{7}$$

where

f_t' = gyroscope integration
f_t'' = vector observation
k = filter co-efficient
a_T = threshold for attaining vector observation in linear accelerations.

The first part of the Eq. (7) maintains a high-frequency response while low-frequency noise is handled by the latter part of Eq. (7). The filter coefficient plays a vital role in drift cancelation rate control. As the values of drift cancelation coefficient increases, drift correction gets slower, however, more accuracy is guaranteed.

The complementary filter integrates the static truthfulness of the accelerometer and gyroscope within vibrant movements. In comparison with Kalman filter, it offers a constant gain.

4.3 KALMAN FILTER

For fusing multisensory data, Kalman filtering is one of the most widely accepted algorithm. Neil Armstrong, reached the moon on his spaceship Appollo, whose navigation computer followed *Kalman filtering*. Though recursive in nature, it shows its worth in the navigational systems of air crafts and in the field of robotics. Mainly this filter is well suited to the entire instrument trade and can be applied in any field requiring data fusion. KDFA gather the past knowledge of the dynamics for prediction of future states. Mathematically KDFA can be expressed as in Eq. (8) (Young, 2009).

$$\vec{x}_{k+1} = A\vec{x}_k + B\vec{u}_k + \vec{\omega}_k \tag{8}$$

where

$\vec{x}_k$ = state vector
A = transition matrix of prior states
B = state matrix of control inputs
ω = noise vector.
If $\vec{y}_k$ is a set of any measured state then it can be expressed as Eq. (9)

$$\vec{y}_k = C\vec{x}_k + \vec{\upsilon}_k \tag{9}$$

In Eq. (9), "C" is the matrix relating to the observed state while $\vec{\upsilon}_k$ is the noise vector.

Given the above-mentioned equations, the Kalman filter can be defined by Eqs. (10)–(12) as in Young (2009).

$$K_k = AP_kC^T(CP_kC^T + R_k)^{-1} \tag{10}$$

$$\hat{\vec{x}}_{k+1} = (A\hat{\vec{x}}_k + B\vec{u}_k) + k(\vec{y} + k + 1 - C\hat{\vec{x}}_k) \tag{11}$$

$$P_{k+1} = AP_kA^T + Q_k + AP_kC^TR_k^{-1} + CP_kA^T \tag{12}$$

where

K = Kalman gain
P = error covariance matrix
Q = uncertainty factor of the system
R_k = covariance matrix of noise vector $\vec{\upsilon}_k$

5 EXPERIMENTAL SETUP

The concept and the usability of data fusion in multiple fields of engineering and computer sciences is not a new thing. However, with emerging new technologies and applications, the said concept needs to be modeled in an efficient and progressive manner. Considering WBASNs, which are rapidly emerging as widely accepted technology, there are different sensors implanted or attached on a body. There are plenty of applications that need orientation sensors, ie, gyroscopes and accelerometers. Continuous sensing results in an enormous amount of data which needs to be analyzed precisely in order to get the desired and accurate results.

The smart phones today are equipped with numerous sensors, most commonly orientation sensors, gyroscopes and accelerometers. These sensors can play a vital role in fall detection and motion capture in relation to e-Health solutions. Sportsmen, often bowlers in cricket, often frequently suffer from backbone injury which can require them to visit a physiotherapist on a daily basis. To investigate improvements, sportsmen have to perform certain biological and motion tests that are expensive and time consuming. If a smart phone is attached to the patient's back that can continuously monitor its bend while walking, sitting or performing any activity this may be a better choice for monitoring the patient's rehabilitation.

In the same way an application is being developed on the basis of a gyroscope and accelerometer (built in sensors of smart phone) that continuously monitors and displays data on the smart phone as well as storing it on the phone's database.

This application is developed using two different data fusion techniques, ie, KDFA and CDFA, to compare results. KDFA comes with a high computational cost and brief history while CDFA is simple and easy to implement. The real-time fused data are collected and results are compared using MATLAB to verify which algorithm performs most efficiently in said scenario.

6 KALMAN AND COMPLEMENTARY FILTERING

6.1 ON TEST BASIS

Before getting real-time data, using Matlab we compared Kalman and Complementary filters to observe computational time, cost and complexity differences. Above all, the performance accuracy was also noted as shown in Fig. 7.

As one can easily see from the Fig. 7, the Kalman filtering results are not especially accurate in comparison with Complementary filtering. However, the Kalman filtering has a brief history in navigational systems, where drifts and angular

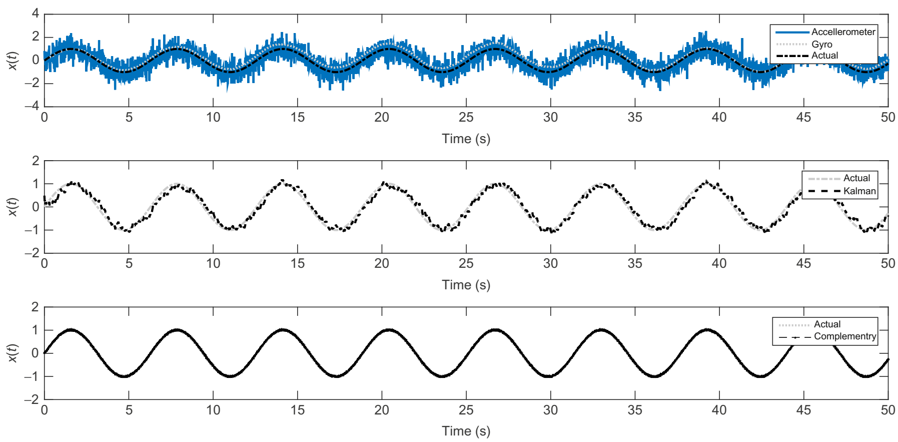

FIG. 7

CDFA and KDFA on test basis.

velocities are easier to predict. In wireless body area sensor fusion (WBASF) it is relatively hard to predict both angular velocity and degree of movement. On the other hand, the Complementary filter has a constant gain that proves its worth in WBASF.

6.2 ON REAL-TIME DATA

Considering the results obtained in Fig. 7, an application is developed fusing the gyroscope and accelerometer data. The results obtained from the accelerometers are depicted in Fig. 8 considering X, Y, and Z axes. Whereas the roll rate, pitch rate and yaw rate of gyroscope are measured as in Fig. 9.

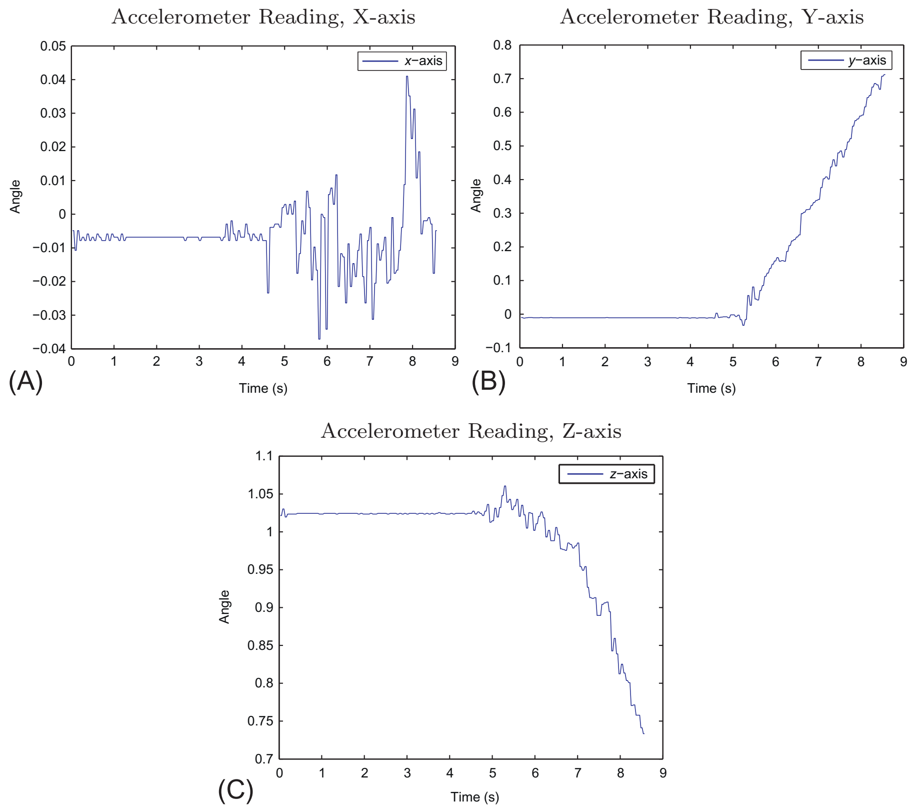

FIG. 8

Accelerometer readings. (A) Accelerometer reading, X-axis. (B) Accelerometer reading, Y-axis. (C) Accelerometer reading, Z-axis.

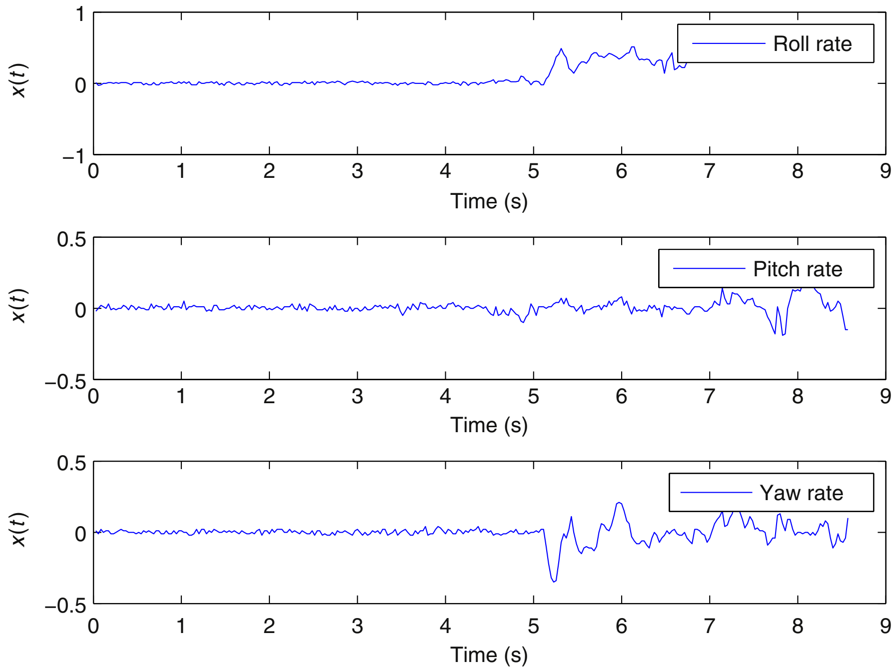

FIG. 9

Gyroscope reading.

6.3 COMPARISON

In accordance with Fig. 10 experimental results show that the Complementary filter outperforms Kalman filter significantly by using less computational and processing power and providing more accuracy. The Complementary filter for WBASF can be applied by having only vector and quaternion mathematical operators. On other hand, the traditional Kalman filter needs an enormous number of matrix operations, including multiplications and taking inverses of these matrices, which, besides the complexity, also results in high computational and processing costs. Moreover, considering WBASF, where prediction of next state is not optimal, the Kalman filter performs badly.

According to the plots illustrated in Fig. 10, along with Eqs. (8)–(12), the Complementary filter supersedes Kalman filtering in the aspect of computational costs. In simple arithmetic manipulations, and trigonometric notations, the Complementary filter bears less than 10% of the computational costs in comparison with the Kalman filter (Simon, 2010; Brückner et al., 2014). Table 2 depicts a comparative analysis of Kalman and Complementary filter techniques for WBASF.

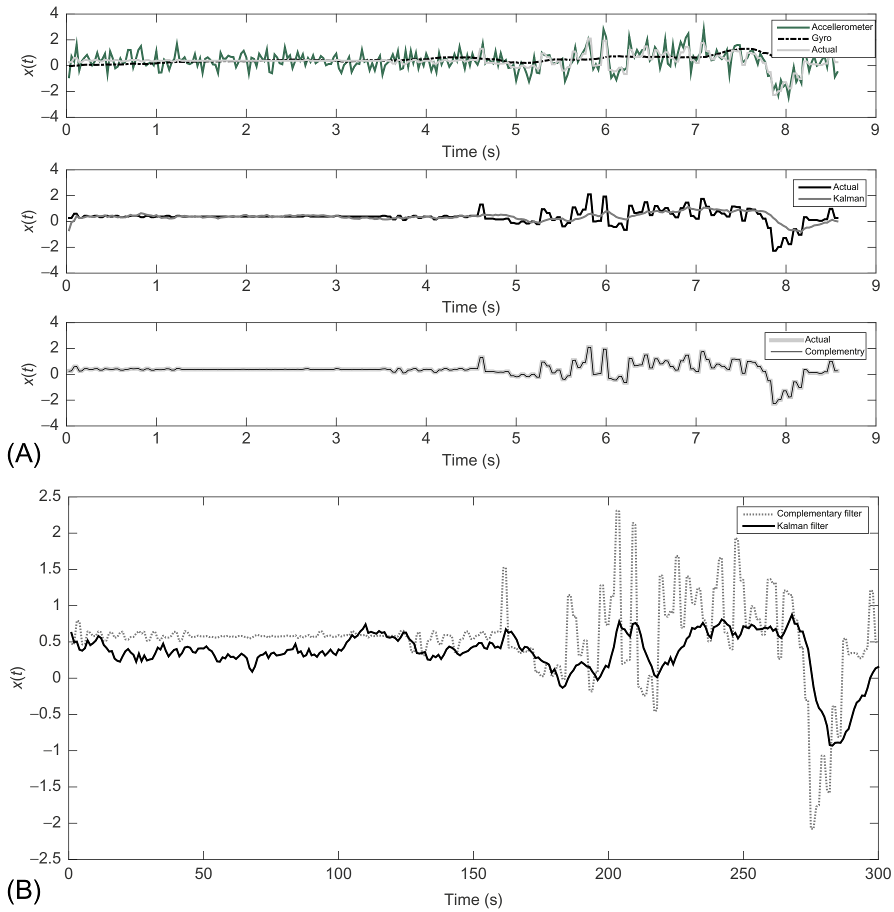

FIG. 10

KDFA vs CDFA as WBASF lgorithms. (A) Original vs KDFA vs CDFA. (B) KDFA vs CDFA.

7 DISCUSSION

What kind of help can a WBASN provide if the data collected are to complex to analyze and diagnose accurately? For this purpose efficient DFAs play a vital and very critical role. In our point of view, without efficient and accurate data fusion techniques WBASNs cannot work efficiently.

Our work is based on the abovementioned statement. Hence the Kalman and Complementary structures in relation to WBASF have been discussed and studied. Generally, the Kalman filtering is used more frequently due to its long history; however, it fails to provide efficient solutions in sensor fusion for BANs considering posture tracking for e-Health solutions. Besides human posture tracking, the Kalman

Table 2 Comparison: CDFA and KDFA

Parameters	KDFA	CDFA
Fusing abilities	Theocratically ideal but not for human body orientation sensing	Clear, noise efficient
Approximation requirements	Physical properties such as mass and inertia required	Rapid estimation of angles, low latency
Coding complexity	Difficult and complex to code	Easy to code
Processor	Much processor intensive	Not very processor intensive
Mathematical complexity	Much complexity, requires linear algebra and matrices calculations	A bit more theory to understand, however simpler
Addition and subtraction	579 times	36 times
Multiplication and division	524+46 times	39+1 times

filter has undoubtedly proven its worth in the navigational and robotics trade where prediction of the next state is not too tricky. Furthermore, calculating and fusing the orientation of different parts of the human body (limbs, legs, back, head, etc.) may require different process models, each with its own parametric values. This is the major reason why in WBASF the Kalman filter fails to predict an accurate approximation of next state. Moreover creating a predefined process model for the different body parts is also a complex task.

Considering Complementary filtering for WBASF, this system does not rely on any assumptions for process dynamics, hence, it does not suffer from the problems that the Kalman filter has to face. Having low complexity and less processing time with zero prediction algorithms, the Complementary filer has proved its worth, as can be seen in the experimental results (Fig. 10). Keeping energy consumption in view, which is one of the major constraints in WBASNs, once again the Complementary filter surpasses the Kalman filter as the processor is capable of much longer low-power sleep timings in comparison with the Kalman filter.

8 CONCLUSION AND FUTURE WORKS

WBASF is an emerging as well as challenging topic in research as well as medical/instrumental industries. Advent of smart phones has taken spot light anticipating its utility as middleware due to its computational, storage and communication capabilities along with built in sensors. Reflecting orientation sensing, numerous DFAs are known and in this work, KDFA and CDFA are analysed considering smart phone as a middle ware. The Kalman data fusing technique has no doubt proven its metal in previous decades for calculating machine orientations. This technique predicts the future state in machines by using past knowledge (aircrafts and robots), although this is a less complex process in this arena. According to our study, work and experiments, when we analyze humans, the future prediction technique of the Kalman filter did not prove its worth. Moreover, its high complexity and computational costs forbid us from using it as a WBASF algorithm. The Complementary filter, in comparison with Kalman filter, shows better performance, with features such as simplicity and low processing, as discussed in Table 2.

In the future we are going to implement the Complementary filter for orientation-based data sensor fusion for patients that suffer back injuries and compare their results with those of the actual rehabilitation tests conducted by physiotherapists.

ACRONYMS

3G	3rd generation
4G	4rth generation
BAN	Body Area Network
CDFA	Complementary Data Fusion Algorithm
CI	Computational Intelligence
DFA	Data Fusion Algorithm
ECG	electrocardiogram
GSM	Global System for Mobile
ICT	Information and Communication Technology
IMU	Inertial Measurement Unit
JDL	Joint Directors of Laboratories
KDFA	Kalman Data Fusion Algorithm
WBASF	wireless body area sensor fusion
WBASN	wireless body area network
WPANs	wireless personal area network
WSN	wireless sensor network

GLOSSARY

Acceleration rate of change of velocity using the basic physics definition.

Accelerometers a sensor/instrument that calculates the velocity of any moving/vibrating body.

Activity monitoring monitoring any activity using any system. In this chapter, it refers to monitoring movement of the body using different sensors.

Angular velocities in classical physics it is the rate of change of angular position.

Assisted living offering a patient help in living with independence, dignity and care.

Body Area Networks a network of wearable/implanted inside body devices that are usually that sense sensing different attributes.
Computational constraints restrictions and limitations on the computing capability of a device, or power or any other.
Computational intelligence refers to the study of designing intelligent decision making devices regarding any specific problem.
Data aggregation summarizing a huge amount of data.
Data Fusion a process that integrates multiple data to provide one concrete, nearly accurate output.
Data Fusion Algorithms algorithms that perform data fusion.
e-Health healthcare practice supported electronically using ICT.
Gyroscopes a sensor that measure angular rotational velocity.
Information and Communication Technology is a parent terminology that includes any communication device integrated with any domain to attain specific results.
Inertial Measurement Unit an instrument composed of multiple sensors used to measure orientation of a body, normally used in aircrafts, spacecrafts, and the finding of any body movement disorders, etc.
Multisensor data fusion refers to fusing data collected from multiple types of sensors.
Orientation sensing states sensing or knowing velocity, acceleration and gravitational forces with respect to the outer world or any specific point.
Velocity in classical physics it is the rate of change in a position with respect to some point of reference.
Wireless body area sensor fusion refers to the fusion of data collected by sensors in a WBAN.
Wireless body area sensor network refers to the network of tiny sensors deployed on/in a body to sense different attributes as per need.

REFERENCES

Abdelgawad, A., Bayoumi, M., 2012. Data fusion in WSN. In: Resource-Aware Data Fusion Algorithms for Wireless Sensor Networks. Springer, Berlin, pp. 17–35.

Bachmann, E.R., McGhee, R.B., Yun, X., Zyda, M.J., 2001. Inertial and magnetic posture tracking for inserting humans into networked virtual environments. In: Proceedings of the ACM Symposium on Virtual Reality Software and Technology. ACM, New York, NY, pp. 9–16.

Bar-Shalom, Y., Fortmann, T.E., Cable, P.G., 1990. Tracking and data association. J. Acoust. Soc. Am. 87 (2), 918–919.

Bar-Shalom, Y., Li, X.R., 1995. Multitarget-Multisensor Tracking: Principles and Techniques, vol. 19. YBS Publishing, Storrs, CT.

Box, G.E., Tiao, G.C., 2011. Bayesian Inference in Statistical Analysis, vol. 40. John Wiley & Sons, New York.

Brückner, H.P., Krüger, B., Blume, H., 2014. Reliable orientation estimation for mobile motion capturing in medical rehabilitation sessions based on inertial measurement units. Microelectron. J. 45 (12), 1603–1611.

Cho, T., Lee, C., Choi, S., 2013. Multi-sensor fusion with interacting multiple model filter for improved aircraft position accuracy. Sensors 13 (4), 4122–4137.

Cockcroft, J., Muller, J., Scheffer, C., 2014. A complementary filter for tracking bicycle crank angles using inertial sensors, kinematic constraints and vertical acceleration updates. IEEE Sens. J. 15 (8), 4218–4225.

Gordon, J., Shortliffe, E.H., 1984. The dempster-shafer theory of evidence. In: Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project, vol. 3, pp. 832–838.

Gordon, N., Ristic, B., Arulampalam, S., 2004. Beyond the Kalman Filter: Particle Filters for Tracking Applications. Artech House, London.

Jayasimha, D., 1994. Fault tolerance in a multisensor environment. In: Proceedings of the 13th Symposium on Reliable Distributed Systems, 1994, IEEE, pp. 2–11.

Khaleghi, B., Khamis, A., Karray, F.O., Razavi, S.N., 2013. Multisensor data fusion: a review of the state-of-the-art. Inform. Fusion 14 (1), 28–44.

Kubo, H., 1992, January. Maximum likelihood sequence estimation apparatus. US Patent 5,081,651.

Lane, N.D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A.T., 2010. A survey of mobile phone sensing. IEEE Commun. Mag. 48 (9), 140–150.

Majumder, S., Scheding, S., Durrant-Whyte, H.F., 2001. Multisensor data fusion for underwater navigation. Robot. Auton. Syst. 35 (2), 97–108.

Mäkisara, K., Simula, O., Kangas, J., Kohonen, T., 2014. Artificial Neural Networks, vol. 2. Elsevier, Amsterdam.

Marquardt, D.W., 1963. An algorithm for least-squares estimation of nonlinear parameters. J. Soc. Ind. Appl. Math. 11 (2), 431–441.

Marzullo, K., 1990. Tolerating failures of continuous-valued sensors. ACM Trans. Comput. Syst. 8 (4), 284–304.

McNeill, F.M., Thro, E., 2014. Fuzzy Logic: A Practical Approach. Academic Press, New York.

Nakamura, E.F., Loureiro, A.A., Frery, A.C., 2007. Information fusion for wireless sensor networks: methods, models, and classifications. ACM Comput. Surv. 39 (3), 9.

Pascu, T., White, M., Beloff, N., Patoli, Z., Barker, L., 2012. Ambient health monitoring: the smartphone as a body sensor network component. InImpact: J. Innov. Impact 6 (1), 62.

Pascu, T., White, M., Patoli, Z., 2013. Motion capture and activity tracking using smartphone–driven body sensor networks. In: Third International Conference on Innovative Computing Technology (INTECH), 2013, pp. 456–462.

Raol, J.R., 2009. Multi-Sensor Data Fusion With MATLAB®. CRC Press, Boca Raton.

Sato, H., 2001, October. Moving average filter. US Patent 6,304,133.

Simon, D., 2010. Kalman filtering with state constraints: a survey of linear and nonlinear algorithms. IET Control Theory Appl. 4 (8), 1303–1318.

Srinivasan, V., 2015. Sensor fusion techniques using extended kalman filter. Int. J. Adv. Eng. 1 (1), 18–22.

Thrun, S., 2003. Learning occupancy grid maps with forward sensor models. Auton. Robot. 15 (2), 111–127.

Walton, D., 2014. Abductive Reasoning. University of Alabama Press, Tuscaloosa, AL.

Want, R., 2014. The power of smartphones. IEEE Pervasive Comput. (3), 76–79.

White, F.E., 1991. Data fusion lexicon. Technical report. DTIC Document.

Young, A., 2009. Comparison of orientation filter algorithms for realtime wireless inertial posture tracking. In: Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 2009. BSN 2009, pp. 59–64.

Zhao, Y., Govindan, R., Estrin, D., 2002. Residual Energy Scans for Monitoring Wireless Sensor Networks. Center for Embedded Network Sensing, UCLA.

Zheng, H., Black, N.D., Harris, N., 2005. Position-sensing technologies for movement analysis in stroke rehabilitation. Med. Biol. Eng. Comput. 43 (4), 413–420.

Zou, W., Sun, W., 2013. A multi-dimensional data association algorithm for multi-sensor fusion. In: Intelligent Science and Intelligent Data Engineering. Springer, Berlin, pp. 280–288.