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"Sensor Fusion: A Review of Methods"

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Abstract: *In the current scenario of the Industry 4.0 era, we are surrounded by the sensors of various type but while we use for the particular application data identification & understanding by controller should be there. This paper aims to present a brief overview of the development of sensor fusion in various application in new coming years, and to understand the various challenges and ability of sensor fusion. Various set of rules that are typically employed are covered to comprehend the complexity of usage in different scenarios.*

Key Words: *Multi-sensor fusion; fusion algorithm.*

1. INTRODUCTION:

Sensor fusion had been a trending-hot area of research in recent years. With the increase of the availability of the numbers and types of sensors, the need arises to manage the increasing quantity of information has produced the need to fuse such data for human to perceive to process for the system. The ability to combine information and integrate them allows for new capability in myriads of areas. Some examples where sensor fusion is now widely engaged in different methods, are automotive automation, mobile robot navigation, and target tracking. Through the integration of multiple sensors, there are certain advantages we can achieve, compared with just a single input. The enhanced reliability, extended parameter coverage, improved resolution is all desirable in any system. While sensor fusion research has improved leaps and bounds in recent years, certainly we are still far away from achieving the competence to mimic the human mind in analyzing different data simultaneously. Due to the multiple sources and types of information being fed continuously, there are various problems that arises, such as data association, sensor uncertainty, and management of data. In most cases, these are usually associated with the inherent ambiguity of each sensors, with device noise and also ambiguities in the environment being measured. A robust system of sensor fusion should be able to handle such uncertainties, and at the end, provide consistent results of the environment.

2. SENSORS, ADVANTAGES/PROBLEM:

Sensors are used to sense the certain attributes or changes of the environment and provide feedback to the system based on its detection/sensing in the form of electrical signal with the use of transducers. Existing sensors that are available include camera, rangefinder, sonar and ultrasonic. In many cases such as mobile devices, they may include accelerometers, magnetometer, ambient air temperature sensors, pressure sensors, gyroscopes, and proximity sensors. The classification of sensors is usually dependent on the purpose, and different criteria can be designated. Some methods which are typically employed to define sensors are between active and passive sensors, absolute or relative, as well as the stimulus of various sensors.

2.1 CHARACTERISTICS OF SENSORS: Most sensors don't directly generate a signal from an external phenomenon, but via several conversion steps. Thus, the output that is read by the user may deviate from the actual input, and these performance-related parameters, or specifications provides information about the deviation from the ideal behavior. There are static characteristics like accuracy, precision, resolution and sensitivity. Typically, these can be easily managed before fusion process. Dynamic characteristics, however, varies between changes of input. The speed and frequency of response, settling time and lag of sensors are all inevitable, and these leads to several of the inherent errors face by sensor fusion. Most sensors are not ideal, and there are deviations which may come into the information required. Some can be assumed to be caused by random noise, which requires signal processing to reduce the error. The other case is a systematic error which is correlated with time, and this can be improved through a defined filter if the error is known.

2.2 ADVANTAGES OF MULTI-SENSOR FUSION: In general, multi-sensor fusion data provides significant advantages as compared to using only a single source data. The improvement of performance is summarized in four general areas [1]: Representation. Information obtained throughout the fusion process has an abstract level, or a granularity, higher than the original individual input data set. This allows for a richer semantic and higher resolution on the data compared to that of each initial source of information. Certainty. We expect the probability of the data to increase after fusion process, increasing the confidence rate of the data in use. The improved signal to noise ratio is also part of the reason of better confidence in the fused data. These are associated with redundant information from group of sensors surveying the same environment. The reliability of the system thus is improved as well in cases of sensor error or failure. Accuracy. If at first data is noisy or have errors, the fusion process should try to reduce or eliminate noise and errors. Usually, the gain in certainty and the gain in accuracy are correlated. The accuracy can be in the timing as well, from the parallel processing of different information from multiple sensors. Completeness. Through bringing new information to the current knowledge of the environment allows for a more thorough view. If individual sensors only provide information that is independent of other sensors, bringing them into a coherent space will give an overarching view of the whole. Usually, if the information is redundant and concordant, the accuracy will improve. The discrimination power of the information is also increased with more comprehensive coverage from multiple sensors. The numbers of sensors which is employed is also a factor in the cost analysis of whether a multi-sensor system is better than a single sensor system [2]. A criterion has to be set up to assess the reliability of the whole system. However, as different applications require different numbers and types of sensor, it is difficult to define an overarching optimal number of sensors for any given system.

2.3 POSSIBLE PROBLEMS AND ISSUES: Certainly, sensor fusion comes with its own inherent problems. Several key issues have to be considered for sensor fusion techniques [3, 4]: Registration. Individual sensors have its own local reference frame from which it provides data. For fusion to occur, the different data sets have to be converted into a common reference frame and aligned together. Calibration error of individual sensors should be addressed during this stage. This problem is critical in determining whether the process of fusion is successful or not. Uncertainty in Sensor data. Diverse formats of data may possibly create noise and ambiguity in the fusion process. Competitive or conflicting data may thus be results from such errors. The redundancy of the data from multiple sensors have to be engaged to reduce uncertainty and learning to reject outliers if conflicting data is encountered. Incomplete, Inconsistent, Spurious data. Data is considered to be incomplete if the observed data remains the same regardless of the number of interpretations. Some methods to make data complete is by either collecting more data features, or through the usage of more sensors. Inconsistent sensors is defined to be two complete data sets but having different interpretations. This is the consequences of bad sensor registration or sensors observing different things. If data contains features that is not related to the observed environment, it is defined to be spurious. Just like uncertainty, the redundancy data have to be exploited to help in fusing the incomplete, inconsistent, and spurious data [5]. Correspondence / Data Association [6, 7]. One aspect of sensor fusion is establishing whether the two tracks from each sensor represent the same object (Track-to track). This is required to know how the data features matches each other from different sensors and knowing whether there are data features that are outliers. The other forms of data association problem is measurement-to-track association, which refers to the problem of recognizing from which target each measurement originates [8]. Granularity. The level of details from different sensors is rarely similar. The data may be sparse or dense, relative to other sensors. The level of data may be different, and this has to be addressed in the process of fusion. Time Scales. In different aspects, sensors may be measuring the same environment at different rates. Another case is two identical sensors measuring at different frequency due to manufacturing defects. The arrival timing at the fusion node may also not coincide due to propagation delays in the system. Especially for spatial distribution of sensors, with variation in the data rate, real-time sensor fusion has to be based on a precise time-scale setting to ensure all data are synchronized properly. In cases where fusion algorithm requires a history of data, how fast the sensor is able to provide data is directly related to the validity of results.

3. ALGORITMS FOR SENSOR FUSION:

Due to the various natures of fusion process, different algorithms are engaged for different level of fusion. These are usually probability theory, classification methods, and artificial intelligence [9].

3.1 KALMAN FILTERING: The Kalman filter is an ideal statistical recursive data processing algorithm which continuously calculates an estimate of a continuous valued state based on periodic observations of the state. See the figure 1 to understand the how Kalman filter will work [20]. It uses an explicit statistical model of how x(t) changes over time and an explicit statistical model of how observations z(t) which are made are related [10, 11]. The explicit description of process and observations lets many models of sensor to be easily incorporated in the algorithm. Not only so, we can constantly assess the role of each sensor in the system. As every iteration requires almost the same effort, the Kalman filter is well adapted for real-time usage.

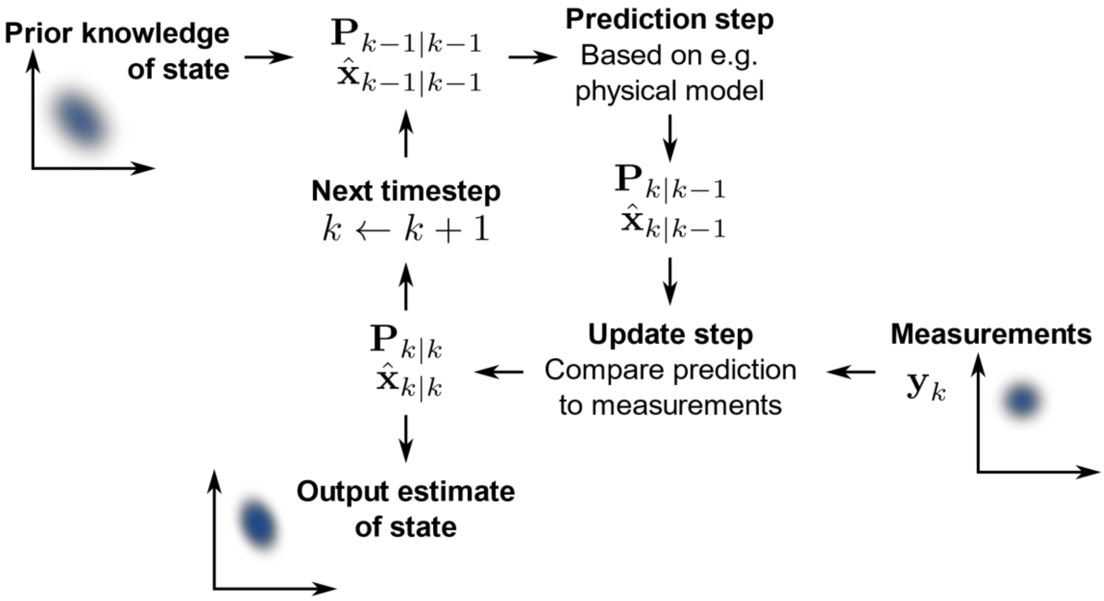

Figure 1 Kalman Filter

The main advantage of Kalman Filter is that it has high computational efficiency since entire sequence of old observations is not reprocessed with every new observation. All these are condensed through the information in the current state and error correlation matrix.

3.2 ARTIFICIAL NEURAL NETWORKS (ANN): ANNs began as an attempt to exploit the architecture of the human brain to perform tasks that conventional algorithms had had little success. They soon reoriented towards improving empirical results, mostly abandoning attempts to remain true to their biological precursors. Neurons are connected to each other in various patterns, to allow the output of some neurons to become the input of others. Figure 2 describe the natural neuron processing in human brain.[21]

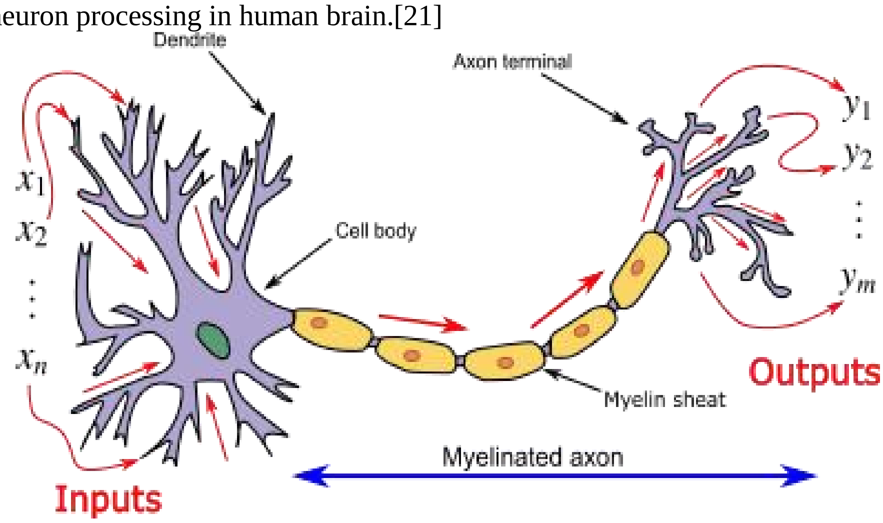

Figure 2 Natural Neuron Processing

ANNs are mathematical models composed of nonlinear computational elements (neurons), operating in parallel and connected as a graph topography characterized by different weighted links. ANNs have proven to be more powerful, and more adaptable method, compared to traditional linear or non-linear analyses [12,13]. The layers of processing neurons can be connected in different ways.[22] The neurons can be trained to learn behavior of any system, using sets of training data and learning algorithms to tune the individual weight of the links. Weights are altered to improve the robustness of the system. Once the errors for the training data have being minimized, the ANNs can remember the functions, and be engaged in further estimations. The data is closely linked with the processing. One major problems currently is determining the best topology for any given problem. Some factors which determines this are the problem itself, the prospective approach to the problem, and the neural network characteristics. Recent research in robot navigation have successfully used neural networks in sensor fusion [14].

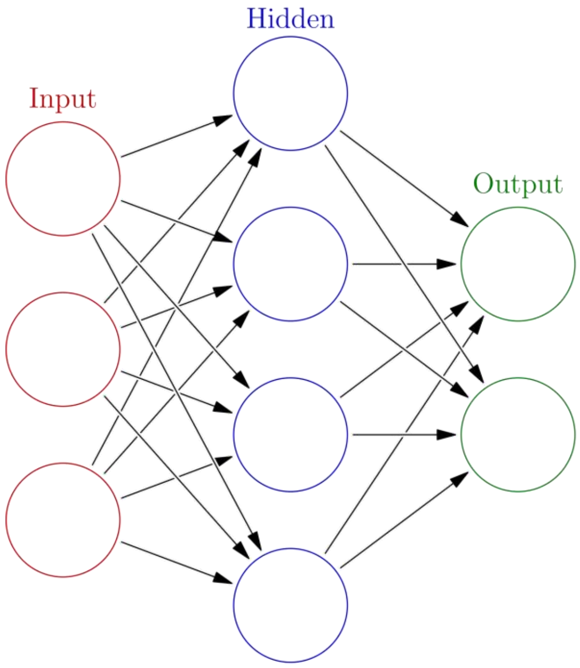

Figure 3 Artificial Neural Network

3.3 FUZZY LOGIC: Fuzzification is the process of assigning the numerical input of a system to fuzzy sets with some degree of membership. This degree of membership may be anywhere within the interval [0,1]. If it is 0 then the value does not belong to the given fuzzy set, and if it is 1 then the value completely belongs within the fuzzy set. Any value between 0 and 1 represents the degree of uncertainty that the value belongs in the set. These fuzzy sets are typically described by words, and so by assigning the system input to fuzzy sets, we can reason with it in a linguistically natural manner.

For example, in the image below the meanings of the expressions cold, warm, and hot are represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot"; i.e. this temperature has zero membership in the fuzzy set "hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold". Therefore, this temperature has 0.2 membership in the fuzzy set "warm" and 0.8 membership in the fuzzy set "cold". The degree of membership assigned for each fuzzy set is the result of fuzzification.[23]

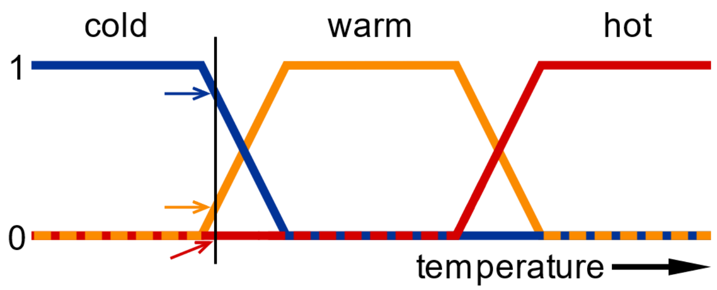

Figure 4 Fuzzy Logic Example of Temperature

Fuzzy logic is finding wide-spread popularity as a method to represent uncertainty in high-level fusion. Essentially, it is a type of multi-value logic that allows the uncertainty in multi-sensor fusion to be categorized in the inference process by assigning each proposition a degree of membership from 0 to 1 [15]. Fuzzy sensor fusion approach has shown a high degree of certainty and accuracy, although the tradeoff is the complex computations required [16].

In most application of sensor fusion, a combination of methods is used to exploit the advantages of artificial intelligence method and traditional method. [17] merges neural network and linearly constrained least squares method, which is shown to be stable and fast. [18] is able to take different information sources with different noise characteristics and achieve optimized results through the use of fuzzy logic. [19] integrate Kalman filter with fuzzy logic techniques and can achieve the optimality of Kalman Filter, and the competence of fuzzy systems to handle inconsistent information.

4. CONCLUSION:

This paper gives a review of sensor fusion theories, from the models of different application of sensor fusion, to some of the common algorithms being used to enable sensor fusion, as well as recent researches that is being carried out. New application areas like Internet of Things, automotive and healthcare applications show benefits when sensor fusion is applied, and there are still a wide range of potential applications that is unable to be covered fully. Certainly, there are still areas of development and research that can help to further advance current level of knowledge. Algorithm fusion is still being debated, to try to focus on the advantages each method has and using new methods to cover up the weakness of other. New approaches to combine the different level of sensor fusion and different approaches have to be developed, and a general framework to assess different sensor fusion technique will be essential to benchmark clearly the different techniques, and to allow us to determine precisely the constraints required for certain system. The accuracy, computational speed and cost of sensor fusion are the three basic requirements, but in most cases today, only two of them are usually fulfilled for every method.

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