Wearable Inertial Sensor for Human Activity Recognition in Field Hockey: Influence of Sensor Combination and Sensor Location

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Abstract. Having a systemic system in recognizing activity in sports is very essential along with enhancing the performance analysis in sport. As the system is required to provide a quality, reliable and unbiased notational data for determining the strength and weakness of field hockey players. Therefore, this study is analysing the accelerometer and gyroscope signal of the four inertial sensors attached to the upper body chest, waist, right and left wrist and formulate the best model in using the wearable sensor for human activity recognition in the field hockey which are passing, drive, drag flick, dribbling, receiving and tackling. Set of features such as mean, standard deviation, maximum and minimum peak are extracted from each inertial sensor signal as an input vector for classification purpose. Results from the study shows that the recognition using combination of all four sensors achieved the highest performance of 96.7% accuracy; and waist and left wrist is recommended if single sensor based human activity recognition is preferred.

1. Introduction

Winning and losing in a match is constantly been related on the performance analysis and process of coaching are conducted during training. Both processes are monitored and analyzed by expert coaches and analysts objectively to improve the performance of player. By definition, performance analysis is to analyze and evaluate the performance of technical, tactical, and physical aspects in training and competition in order to (1) understand which areas need to be focused [1], (2) identify the strengths and weaknesses of player [1, 2], (3) identify the early cues of injury [2] and (4) create a well-planning strategy [1]. In general, two different disciplines, notational analyst and bio-mechanist studied the performance analysis. However, notational analyst work has become the motivation in this study. Generally, notational analyst will provide statistical data, mostly known as notational data regarding to the performed activities by players during training or competition. A well-planned strategy and good tactical performance are effectively established from the reliable and useful information of notational data interpreted by coaches. Thus, by having accurate data is very necessary to observe the progress and provide the right physical assessment to players. For instance, work in [3] studied the successful soccer team using notational data. But, the data collection was practicing the observational method and did proven that the performance of the
match was related with the information of notational data. However, observational method is unreliable and inaccurate due to overlooked, bias and human error. Therefore, a system of activity recognition is suggestively required to overcome the limitations.

Based on previous studies, systems of automated human activity recognition were studied using two different modalities: 1) Video based sensor; and 2) Wearable sensor. Initially, study of human activity recognition was introduced using video based sensor. The video sensors are generally attached to the environment for monitoring the player while performing either during the training or the game and human activity is recognized from the live or recorded video match [4]. However, using video based sensor in recognizing human activity might suffer with high computational complexity as the development of the system is dealing high volume of image frame or video as the input of the system. Meanwhile, the human activity based on wearable sensor use less dimensional data consists of several signals that represent the human activity. Therefore, this study has utilized inertial sensor in recognizing the human activity in field hockey.

An advanced wearable sensor technology is quietly growing attention within activity recognition study. Wearable sensor modality, particularly inertial, accelerometer, gyroscope and magnetometer are the common sensor used for activity classification, monitoring and recognition as well. In addition, few commercialized products such as Catapult and GPSports currently design miniature wearable sensors embedded with global positioning system (GPS), accelerometer and gyroscope for sports study. The development of latest technology should be in line with human daily life in order to improve and prevent bias and errors of human doing. Previous activity recognition works focused on the potential of inertial sensor in many diverse human applications. Especially monitoring human daily ambulation such as standing, sitting, lying and walking [5, 6], rehabilitation [7, 8] and etc. Some of the issues in using wearable sensor to recognize the human activity are the number of sensor need to be used and the location of sensor on the human body. Too many sensors on human body are not practically recommended, as it will make uncomfortable and difficult for players to perform a movement. Increasing the number of sensor or choosing the appropriate sensor location will increase the performance of recognizing the human activity. Therefore, this study is was focused on analysing the accelerometer and gyroscope signal of four inertial sensor attached to the upper body chest, waist, right and left wrist and formulate the best model in using the wearable sensor for human activity recognition in the field hockey.

2. Related study

There are several works that were done in using the wearable sensor to recognizing human activity for sport application. In field hockey, the work by Mitchell et al. [9] utilized an embedded accelerometer sensor in smartphone to recognize the changes of back of body in recognizing the such as hitting ball, standing tackle and dribbling. Thiel et al. deployed an accelerometer sensor onto hockey stick to monitor the speed of stick [10]. In ice hockey, a single 3D accelerometer sensor was positioned on the right hockey skate and algorithm studied by Stetter et al. [11] objectively to detect the initial contact time and blade-off time from accelerometer signal. Meanwhile, work in [12] utilized accelerometer readings to recognize seven ice hockey activities. However, works [10, 11] were not focusing on the human activity recognition. Other than that, wearable sensor has been utilized for activity recognition in other various sports, for instance soccer [9, 13-15], badminton [16-18], volleyball [19], beach volleyball [20], baseball [19], tennis [21, 22], rugby [23, 24], table tennis [25], skateboard [26], snowboarding [27], basketball [28], cricket [29], weightlifting...
[30] and golf [31]. Most of the previous sport activity recognition works were based on a single accelerometer sensor or a single fusion of accelerometer and gyroscope sensors.

| Sport       | References          | Sport activity recognition | Single-sensor based study | Multiple-sensor based study | Accuracy          |
|-------------|---------------------|----------------------------|---------------------------|-----------------------------|------------------|
| Rugby       | [23] Kautz, Groh et al. (2015) | Chest                     |                           | 97.2% by Naïve Bayes        |
|             | [24] Kelly, Coughlan et al. (2012) | Back of body              |                           | 76.1% by support vector machine |
| Field hockey| [9] Mitchell et al. (2013) | Back of body              |                           | 65.9% by support vector machine |
| Ice hockey  | [12] Hardegger, Ledergerber et al. (2015) | Shoelaces of the skate     |                           | 92.0% (skating) 92.9% (shooting) |
|             | [13] Schuldhaus et al. (2015) | Soccer shoes              |                           | 84.2% by support vector machine |
| Soccer      | [9] Mitchell et al. (2013) | Back of body              |                           | 62.7% by support vector machine |
|             | [15] Zhou, Koerger et al. (2016) | Soccer shoes              |                           | 94.6% by Naïve Bayes        |
|             | [14] Dorschky, Schuldhaus et al. (2015) | Soccer shoes              |                           | 99% by Random forest + Hidden Markov model |
|             | [16] Wang et al. (2016) | Left and right wrist      |                           | 97.96% by Hidden Markov model |
| Badminton   | [17] Anik, Hassan et al. (2016) | Racket                    |                           | 88.89%                      |
|             | [18] Rusydi, Huda et al. (2016) | Wrist                     |                           | N/A                         |
| Volleyball  | [19] Rawashdeh, Rafeldt et al. (2015) | Upper arm                |                           | 94.04% by decision tree     |
| Beach volley| [20] Kautz et al. (2017) | Wrist                     |                           | 83.2% by deep learning      |
| Baseball    | [19] Rawashdeh, Rafeldt et al. (2015) | Upper arm                |                           | 94.04% by decision tree     |
Table 1 summarizes the existing works that applied the wearable sensor for recognizing the human activity in sport with several different sensor location and number of sensor used to recognize sport activity. Most of the works that deployed with multiple-sensor have achieved an excellent performance which is higher than 80.0%. However, example studies that working on single-sensor, such as [9, 24] has relatively achieved low performance of accuracy when compared to the works in [17, 19-21, 23, 25]. This is due to the selecting an appropriate sensor location might also effect the performance of the recognition system. Since, the number of sensor used and sensor location are apparently subjective issues and yet do not have a proper justification towards the establishing a system of recognizing activity in field hockey. Therefore, this study analyses the wearable sensor for automated human activity recognition in field hockey in terms of the number of sensor and sensor location using machine learning approaches.

3. Methodology
This section discussed the proposed method for activity recognition in field hockey using two different sensor based study. Figure 1 shows a general workflow that used in this study.

![Figure 1. General workflow of study.](image)

3.1. Data Collection and signal synchronization
In data collection, four Physilog® 4 Silver inertial sensors were attached at chest, waist, left and right wrist of player using Velcro strap. In this study, the accelerometer and gyroscope signal were obtained from the sensor while the subject was performing the activity in field hockey. The sampling frequency used for field hockey activity recognition was set to 200Hz. 11 players were involved in this study to perform 22 specific field hockey activities. Each specific activity is classified into six general activities which are passing, drive, drag flick, dribbling, receiving and tackling. Each activity was performed in controlled environment with
repetition of three times. For activity annotation, this study required a video footage. The acquired video footage performing the activity is intending to synchronize with signals from inertial sensor. The reason was to avoid biasing and error during activity annotation of field hockey.

3.2. Sliding of fixed segmented window
In this state, the collected signals were segmented with window period of 0.64 second according to our previous work in [32]. Previous works [33, 34] show that segmentation process is essential in signal processing as it contributed to the activity recognition system. Equation (1) illustrates the number of samples is segmented within window period.

\[
\text{Window period, } s = \frac{\text{Window size}}{\text{Sampling frequency,} \text{Hz}} \tag{1}
\]

In the segmentation process, the labelled signal was segmented using a fixed-width sliding windows with 50 % overlap. In this study, window overlapping is necessary and intended to be applied in the transition of signal for more accurately as sports movements are physically vigorous and rugged.

3.3. Features extraction in time domain
Statistical features in time-domain were used to extract information within the signals. Mean, standard deviation, maximum and minimum features were extracted and creating a feature vector. Therefore, 4 features from 6 signals (accelerometer and gyroscope signals) x 4 statistical features were used for classification algorithm in human activity recognition for field hockey. The following equations represent time-domain features:

\[
\text{Mean equation, } \mu = \frac{1}{n} \sum_{i=1}^{n} a_i \tag{2}
\]

\[
\text{Variance equation, } \sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} |a_i - \mu|^2} \tag{3}
\]

Minimum peak equation, \( a_{\text{min}} = \min_{i \in \{1, 2, 3, \ldots, n\}} a_i \tag{4} \)

Maximum peak equation, \( a_{\text{max}} = \max_{i \in \{1, 2, 3, \ldots, n\}} a_i \tag{5} \)

3.4. Data train and performance
In this study, several combinations of the aforementioned four wearable sensors located on different body location were investigated for activity recognition system in field hockey. 10-fold cross validation method (90% of data for training and 10% of data for testing) were set for each classifier. Four different classifiers framework intended to search the best learning for activity recognition. The classifiers that were used for training and testing in this study are decision tree, support vector machine (SVM), K-nearest neighbor (K-NN) and ensemble. In the beginning, the combination of all four sensor was evaluated these four classifier. After that, the best classifier in term of accuracy rate was selected to investigate the appropriate number of sensor and sensor location within four sensors in recognizing human activity in field hockey.
4. Result and discussion

Performance of Four Inertial Sensors in Recognizing Field Hockey Movements

Figure 2. Performance of four inertial sensors with different classifiers learning.

As result, varies of classifiers were trained and tested with given processed input signal and features. Figure 2 shows the result of four inertial sensors towards the performance of 21 classifiers. The deployment of four sensors has resulted Cubic SVM with best performance 96.7%. Comparing, with lowest performance, resulted by the performance of Fine Gaussian SVM with 52.1 %.

Table 2. Accuracy Cubic SVM for single-sensor and multiple-sensor based study

| Fusion of sensor location | Cubic SVM Accuracy (%) |
|--------------------------|------------------------|
| Chest * Right Wrist * Waist * Left Wrist * | 65.5 |
| Chest * Right Wrist * Waist * Left Wrist | 63.8 |
| Chest * Right Wrist * Waist * Left Wrist | 89.8 |
| Chest * Right Wrist * Waist * Left Wrist | 86.2 |
| Chest * Right Wrist * Waist * Left Wrist | 75.3 |
| Chest * Right Wrist * Waist * Left Wrist | 94.8 |
| Chest * Right Wrist * Waist * Left Wrist | 93.7 |
| Chest * Right Wrist * Waist * Left Wrist | 93.3 |
| Chest * Right Wrist * Waist * Left Wrist | 89.6 |
| Chest * Right Wrist * Waist * Left Wrist | 94.2 |
Table 2 is stressing on the performance of Cubic SVM along with number of sensor used and sensor location. Each sensor location, chest, waist, right and left wrist was analyzed independently to observe and compare the performance of each sensor. As shown in Table 2, inertial sensor signal on waist and left wrist has achieved the best performance, 89.8% and 86.2% accuracy. Nevertheless, the performances of signal on chest and right wrist have yield 65.5% and 63.8% accuracy respectively. The performance of Cubic SVM begins to incline as the inputs from different sensors location were combined. For two sensors combination, the fusion between chest and waist has achieved the highest performance with 94.8% accuracy meanwhile accuracy of 75.3% resulted from chest and right wrist. The increment of accuracy was due to the center location of sensor within human body that carried useful information for activity recognition of field hockey. The field hockey activity was performed mostly using left hand, therefore it can be concluded that left wrist has the higher performance compared with right wrist, while sensor on waist is more stable than chest as most of activity in field hockey produce significant uncertain movement of chest. For three sensors combination, the performance of Cubic SVM is increasing up to 95.8% yielded by chest, waist and left wrist. Overall, from the result, performance of activity recognition system within field hockey significantly increased as the multiple-sensor is combined.

5. Conclusion
As conclusion, the proposed algorithm in this study managed to classify passing, drag flick, drive, dribbling, receiving and tackles with single-sensor and multiple-sensor based study. The number of sensors used and sensor location are really important as proven in this study. The study of number of sensors used and location for monitoring and classification was intended to improve classification accuracy. From the result, combination of four inertial sensors has resulted the better classification accuracy in a wide range of six field hockey activities compared with single-sensor based study. However, if single sensor is preferred, the waist and left wrist is recommended as both locations provide high accuracy in recognizing the activity.

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