# Automatic Activity Classification and Movement Assessment During a Sports Training Session Using Wearable Inertial Sensors

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***Abstract*—Motion analysis technologies have been widely used to monitor the potential for injury and enhance athlete performance. However, most of these technologies are expensive, can only be used in laboratory environments and examine only a few trials of each movement action. In this paper, we present a novel ambulatory motion analysis framework using wearable inertial sensors to accurately assess all of an athlete's activities in an outdoor training environment. We firstly present a system that automatically classifies a large range of training activities using the Discrete Wavelet Transform (DWT) in conjunction with a Random forest classifier. The classifier is capable of successfully classifying various activities with up to $98\%$ accuracy. Secondly, a computationally efficient gradient descent algorithm is used to estimate the relative orientations of the wearable inertial sensors mounted on the thigh and shank of a subject, from which the flexion-extension knee angle is calculated. Finally, a curve shift registration technique is applied to both generate normative data and determine if a subject's movement technique differed to the normative data in order to identify potential injury related factors. It is envisaged that the proposed framework could be utilized for accurate and automatic sports activity classification and reliable movement technique evaluation in various unconstrained environments.**

***Keywords*— Activity classification; Technique assessment; Sensor fusion; Knee joint angle; Curve shift registration**

## I. Introduction

Sport and physical activity have important cardiovascular, musculoskeletal and mental health benefits [1] and are enjoyed by large numbers. However, associated lower body musculoskeletal injuries are very common [2], [3], [4]. Almost all injuries are caused by relative excessive loading on the tissues i.e. high loading relative to tissue strength. One factor that significantly influences this loading is movement technique. Athletes can be biomechanically screened to determine an athlete's predisposition for injury [5] by recording and quantifying both their movement technique (i.e. joint angle and angular velocity) and some measure[1] of loading on their lower body during a series of actions common to their sport and known to be related to injury (e.g. running [3], jumping and landing [6], agility cuts [7]). Generally, the athlete completes $3-5$ maximum effort trials of each action [6] and their results are compared to normative values, if available [8]. These tests are almost exclusively completed in a laboratory since biomechanics based motion analysis systems tend to be camera based (6+ cameras typically) which must remain spatially fixed during the testing session and tend to be negatively affected by changing lighting conditions. This screening process creates several assessment and comparison challenges, which significantly reduce its ecological validity and usefulness. These include:

1. The athletes are generally highly focused on how they complete the tasks, and therefore may not utilize a movement technique that they would normally use in a training session or match.
2. The controlled laboratory environment does not reflect the conditions of the training environment (e.g. uneven/wet ground, fatigued conditions).
3. The use of only 1 to 5 trials as representative of how an athlete completes a movement technique is highly questionable. The low number of trials is common because of the significant processing time (and cost) associated with optical based systems.
4. There is a lack of normative data for many sports based tasks.
5. It is a very expensive process limiting its general application.

A solution to the above assessment challenges would be to use sensors that could be worn throughout a training session or competitive event, detecting an athlete's joint angular motion and impact accelerations. Accelerometers mounted on the body can be used to infer loading based on Newton's second law of motion $(F=ma)$[6] during every foot-ground contact. We estimate that within a 45 minute training session this could involve each foot striking the ground ($>2000$) times. With the recent development of more accurate and relatively cheap wireless/wearable inertial motion units (WIMUs), combined with improved algorithms to more accurately determine sensor orientation [9], [10] , it has become feasible to deploy wearable body sensor networks in training sessions. Some commercially

[1] Direct loading on individual tissues cannot be measured in a non-invasive fashion but this is possible for aggregate loading on a region of tissues or structures.

available systems include Xsens (www.xsens.com) and Shimmer (www.shimmersensing.com). If WIMUs are to be used in this context, data processing time must be very short and user involvement minimized. This requires a system to automatically and accurately categorize each foot-ground contact based on the type of movement of the user (i.e. walk, jog, sprint, jump, land, agility cut). Even with low trial numbers, there are a number of challenges associated with comparing data (which are amplified with the larger trial numbers potentially possible with WIMUs):

6. Continuous data (e.g. joint angle) are usually reduced to a single/few discrete measure(s) that purportedly represent a joint's movement technique (e.g. peak flexion), but in reality comprises less than 2% of the available data [11], [12].

7. Continuous data (e.g. angle-time data) contains phase and amplitude variations both between individuals (inter-subject) and within multiple trials by the same individual (intra-subject).

Traditionally normative data is produced by time normalizing a trial to 101 data points and averaging across trials (e.g. mean $\pm 95\%$ confidence intervals) [8]. However, this can result in a distortion of the data as key events are not time aligned across trials [12].

These last two challenges can potentially be addressed using continuous data analysis techniques (e.g. functional data analysis [13]), although only a handful of biomechanical studies have attempted to do so [14], [11]. The aim of this study is to utilize wearable inertial sensors and develop a method to:

- Automatically and accurately categorize each foot-ground contact based on the type of movement (i.e. walk, jog, sprint, jump, land, agility cut);
- Extract joint kinematic data and impact acceleration data automatically for each foot contact cycle;
- Generate normative data using a functional data approach;
- Compare an individual to the normative data and identify the phase over which they differ (if any).

## II. Proposed Framework

The main components of our framework are illustrated in Fig 1. It consists of three main components: activity classification, sensor orientation and flexion-extension knee angle calculation and technique analysis. We present results only in relation to a single variable (i.e. knee flexion-extension) in order to exemplify the process and avoid unnecessary repetition in this paper.


Fig. 1. The main components of the proposed motion analysis framework

### A. Activity Classification

Automatic activity classification is used to identify different training activities as this would allow training sessions to be more quickly evaluated by sporting and health professionals. It would allow them to quickly segment an athlete's training session by activity and thus allow the desired data to be more easily located. This approach also facilitates the creation of a database containing the evolution of an athlete's movements within and across training sessions.

Much of the prior research in activity classification has dealt with identifying mundane tasks such as eating, ascending and descending stairs, sitting, brushing teeth as well as motion activities such as being stationary, walking and running [15], [16] and training exercises and sports activities [17], [18]. Current research has shown that accelerometers can be used to classify human activity for high energy actions such as sprinting, jogging, jumping, etc. [19]. In sports, accelerometers have been used to monitor elite athletes in competition and training environments. In swimming applications, accelerometers have allowed the comparison of stroke characteristics for a variety of training strokes and therefore have helped to improve swimming technique [20]. In competitive rowing, they have been used for the recovery of intra- and inter-stroke phases as a means to assess technique [21]. Accelerometers have also been utilized to identify the various phases of Kinematic chain during the serve action in tennis [22].

In developing our approach to activity classification, the exercise routine performed by each athlete was segmented and annotated for all activities and used to create a training set. A window length of three seconds was chosen as this was sufficient time for each of the selected training activities to be completed. The Discrete Wavelet Transform (DWT) has been used with much success in extracting discriminative features from accelerometer data as the basis for classification. It has been used to assist in identifying sporting activities in soccer and field hockey [23]. Daubechies 4 wavelet "db4" is a popular mother wavelet choice in signal analysis problems due to its regularity and fast computational time, and was chosen in this work. The total energy $E_T$ at level $i$ of the DWT decomposition is given by [15].

$$E_T = A_i A_i^T + \sum_{j=1}^{i} D_j D_j^T \tag{1}$$

where $A_i$ is the approximation coefficient at level $i$ and $D_i$ is the detailed coefficient at level $i$. One feature proven to be useful in discrimination is the energy ratio in each type of coefficient [15]. $EDR_A$ represents the energy ratio of the approximation coefficients while $EDR_{Dj}$ represents the energy ratio of the detail coefficients.

$$EDR_A = \frac{A_i A_i^T}{E_T} \tag{2}$$

$$EDR_{D_j} = \frac{D_i D_j^T}{E_T} \qquad j = 1, \ldots, i \tag{3}$$

In [15], Ayrulu-Erdem and Barshan found that the normalized variances of the DWT decomposition coefficients and the EDRs provided the most informative features for a different albeit similar problem. They contrasted their performance to informational features such as normalized means, minimums and maximums of the EDRs and obtained superior performance. As such we adopt the same approach here. The variances of the coefficients are calculated over each DWT coefficient vector at the $i^{th}$ level. A random forest training algorithm in conjunction with the DWT features was employed to create an appropriate classifier. Other classifiers were investigated however the Random Forest achieved the highest classification accuracy within acceptable computational limits.

### B. Sensor Orientation and Knee Joint Angle Estimation

Measuring accurate orientation plays an important role in sports activity applications as it enables coaches, biomechanists and sports scientists to monitor and investigate athletes' movement technique in outdoor environments. Although there are different technologies to monitor athletes' technique and measure their body orientation, wearable inertial sensors have the advantage of being self-contained in a way that measurement is independent of motion, environment and location. It is feasible to measure accurate orientation in three-dimensional space by utilizing tri-axial accelerometers, and gyroscopes and a proper filter.

The Kalman filter has widely been utilized to measure orientation for many applications and commercial inertial orientation sensors, including Xsens and Intersense [24], [25]. However, it has some disadvantages including implementation complexity [26], [27], high sampling rate due to linear regression iteration (fundamental to the Kalman process) and the requirement to deal with large scale vectors to describe rotational kinematics in three-dimensions [25], [10]. There are some other alternatives to address these issues including Fuzzy processing [28] or frequency domain filters [29]. Although these approaches are easy to implement, they are limited to operating conditions. In this paper, we use an algorithm which has been shown to provide effective performance at low computational expense. Using such a technique, it is feasible to have a lightweight, inexpensive system capable of functioning over an extended period of time.

The algorithm employs a quaternion representation of orientation [9] and is not subject to the problematic singularities associated with Euler angles. The estimated orientation rate is defined in the following equations [9]:

$$\begin{cases} {}^S_E q_t = {}^S_E q_{t-1} + {}^S_E \dot{q}_t \Delta t \\ {}^S_E \dot{q}_t = {}^S_E \dot{q}_{\omega,t} - \beta \frac{\nabla f}{||\nabla f||} \end{cases}, \tag{4}$$

where

$$\begin{aligned} &\nabla f({}^S_E q, E_g, S_a) = J^T({}^S_E q, E_g) f({}^S_E q, E_g, S_a) \\ &S_a = [0, a_x, a_y, a_z] \\ &E_g = [0, 0, 0, 1] \end{aligned} \tag{5}$$

In this formulation, ${}^S_E q_t$ and ${}^S_E q_{t-1}$ are the orientation of the Earth frame relative to the sensor frame at time $t$ and $t-1$ respectively. ${}^S_E \dot{q}_{\omega,t}$ is the rate of change of orientation measured by the gyroscopes. $S_a$ is the acceleration in the $x$, $y$ and $z$ axes of the sensor frame, termed $a_x$, $a_y$, $a_z$ respectively. The algorithm calculates the orientation ${}^S_E q_t$ by integrating the estimated rate of change of orientation measured by the gyroscope. Then gyroscope measurement error, $\beta$, was removed in a direction based on accelerometer measurements. This algorithm uses a gradient descent optimization technique to measure only one solution for the sensor orientation by knowing the direction of the gravity in the Earth frame. $f$ is the objective function and $J$ is its Jacobean.

In order to measure flexion-extension knee joint angle, the orientation of the two wearable inertial sensors attached on the thigh and shank were calculated using the described fusion algorithm. Then a technique based on a leg movement was used to align the reference frame of the two sensors [30]. Typically a joint rotation is defined as the orientation of a distal segment with respect to the proximal segment. This can be applied to the shank and thigh segments to calculate knee joint angles [31]. This is described by the following equation:

$$q_{knee} = {}^S_E q^*_{thigh} \otimes {}^S_E q_{shank} \tag{6}$$

where ${}^S_E q_{thigh}$ and ${}^S_E q_{shank}$ are the quaternion representation of the orientation of the thigh and shank respectively. The $\otimes$ denotes the quaternion product and $*$ denotes the quaternion conjugate. The knee joint angles were measured during the entire training session. The results are illustrated and discussed in section III-C.

### C. Technique Analysis

The exercise reported in detail in this section is the jogging task. This was selected because it incorporates three activities that can make up most actions: an impact (with the ground), a loading phase and a swing (unloaded) phase. The jogging task was extracted based on the information given by the classification approach reported above. Foot contact cycles (heel strike to heel strike) were identified using knee joint angles and tibial acceleration. Heel strike was defined as the sudden change in acceleration after every cyclic local maximum in knee joint angle data (i.e. the swing phase). The separated knee joint angle curves demonstrated similar patterns which, as expected, differed in their temporal characteristics. To maintain all the information of the curve shapes (magnitude and timing of local maxima and minima) the normative (representative) curve was created using two approaches: (a) averaging across the foot contact cycle without registration (unregistered curve), which is the most common approach in biomechanics [32], [33] and (b) performing a phase shift registration approach before averaging across the foot contact cycles as described by the following equations [13]:

$$x^*_i(t) = x_i(t + \delta_i) \tag{7}$$

$$\begin{aligned} SSE &= \sum_{i=1}^{N} \int_\tau ([x_i(t+\delta_i) - \hat{\mu}(t)]^2 ds) \\ &= \sum_{i=1}^{N} \int_\tau ([x^*_i(t+\delta_i) - \hat{\mu}(t)]^2 ds) \end{aligned} . \tag{8}$$

The phase shift registration alters the time domain by $\delta_j$ for each waveform $x$ within a foot contact cycle $i$ for multiple $\delta_j$ to find the $\delta_j$ where a registration criteria is at its minimum [13]. The used criterion (squared standard error; $SSE$) was calculated for each waveform relative to the overall mean $\hat{\mu}(t)$ over its specific time interval $t$. This process was applied for every foot contact cycle to identify the optimal $\delta_j$ for each foot contact cycle $i$. Subsequently, these curves were registered using the optimal $\delta_j$. After all waveforms were registered, the overall mean was updated and the whole process was iterated $n$ times until no significant change ($SSE_n \ll SSE_n \approx SSE_n$) in the registration criteria occurred. This procedure of estimating a transformation by transforming to an iteratively updated average is often referred to as the Procrustes method [13][2]. To examine if differences exist between the mean curve and the registered mean curve, we examined the curves using Analysis of Characterizing Phases [11]. This approach offers a more comprehensive comparison than discrete point analysis or functional principal component analysis.

To explore the ability of the proposed process to identify individuals with abnormal movement biomechanics, an individual with low back pain was also assessed. Clinical differences were explored both visually and statistically (where significance is indicated by the mean and confidence intervals of the single athlete laying outside the $95\%$ confidence intervals of the normal group data [34]).

## III. Experiments and Evaluation

### A. Data Collection

To evaluate the proposed framework, recordings of nine healthy subjects and one injured subject whose actions were captured using four wearable inertial sensors. WIMUs were placed on the left/right shank and left/right thigh of a subject as shown in Fig.2. The location of the sensor on each body segment was chosen to avoid large muscles; as soft tissue deformations due to muscle contractions and foot-ground impacts may negatively affect the accuracy of joint orientation estimates. The sensors were affixed to the subject with double sided tape and velcro straps with some elasticity in the fabric, so as not to restrict the subject's movement and performance in any way. Next, the subject was asked to perform a series of actions as they normally do during outdoor training sessions. Each subject performed a predefined exercise routine on a large outdoor grass soccer pitch. The exercise routine consisted of the following motions: agility cuts, walking, sprinting, jogging, box jumps and football free kicks. Each motion lasted approximately $60$ seconds for a total of approximately $9-10$ minutes for the entire session.

The data from each sensor was recorded to an internal SD card on board the device. As each sensor recorded data independently, a physical event was required to synchronize all devices together. This was achieved by instructing each subject to perform five vertical jumps, ensuring large acceleration spikes would occur simultaneously on each device, that would be clearly visible in the accelerometer stream. In a post processing step, peak alignment was automatically performed and all data streams were cropped to two seconds before the first vertical jump landing. Video footage of each data capture session was also recorded and annotated, to be used as ground truth for the automatic segmentation and recognition of movements categories (i.e. jogging, agility cuts, sprinting etc.).

[2]The reader should note that for some biomechanical data (or waveforms) phase shift registration might not lead to a representative curve shape. For such cases a dynamical time warping approach can be applied, which uses specific landmarks (global maxima and minima) to define a warping function $h$ to which the waveforms are evaluated (Equation $x_i^*(t) = x_i[h_i(t)]$)

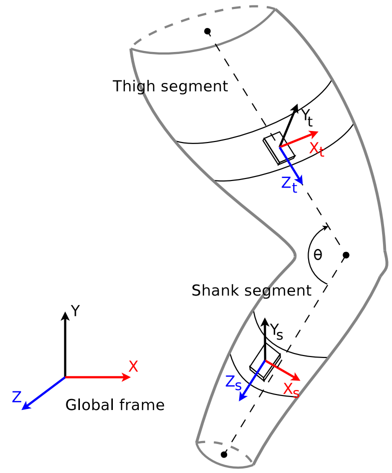


Fig. 2. Placement of two inertial sensor units on the thigh and shank as well as their local coordinate system in a global coordinate system is illustrated.

### B. Classification Evaluation

Using the approach described in section II-A, we achieved a classification accuracy of $98.3\%$. This value was computed using a ten-fold cross validation leave one out method. The F-measure score, as a harmonic mean of precision and recall that reaches its best value at $1$ and worst score at $0$, was calculated. Precision is calculated as the number of correct results divided by the number of total results while recall is the number of correct results divided by the number of results that should have been returned positive. These metrics are often described in terms of the metrics true positive ($T_p$), false positive ($F_p$) and false negative ($F_n$). Since the classifier was trained with classes which had different instance populations the F-measure scores are given in table II. The F-measure score gives a better indication of a models ability to correctly identify an activity than standard classification accuracy alone.

Table I shows the confusion matrix from the classification procedure. There is only one area of confusion using this model which is kicking the football. This difficultly lies with the variation in kicking styles from person to person. As can

TABLE I. Confusion matrix for the classifier

| **Activity** | **a** | **b** | **c** | **d** | **e** | **f** |
|---|---|---|---|---|---|---|
| **a** = Agility cut | 180 | 0 | 0 | 0 | 0 | 0 |
| **b** = Walking | 0 | 399 | 0 | 0 | 0 | 0 |
| **c** = Jumping on box | 0 | 0 | 27 | 2 | 0 | 0 |
| **d** = Jogging | 0 | 0 | 0 | 205 | 0 | 0 |
| **e** = Sprinting | 0 | 0 | 0 | 0 | 28 | 0 |
| **f** = Kicking | 3 | 5 | 2 | 3 | 1 | 73 |

TABLE II. The precision, recall and F-measure from the classifier applied to the activities during training sessions.

| **Activity** | **Precision** | **Recall** | **F-measure** |
|---|---|---|---|
| **Agility cut** | 0.984 | 1 | 0.992 |
| **Walking** | 0.988 | 1 | 0.994 |
| **Jumping on Box** | 0.931 | 0.931 | 0.931 |
| **Jogging** | 0.976 | 1 | 0.988 |
| **Sprinting** | 0.966 | 1 | 0.982 |
| **Kicking** | 1 | 0.839 | 0.913 |

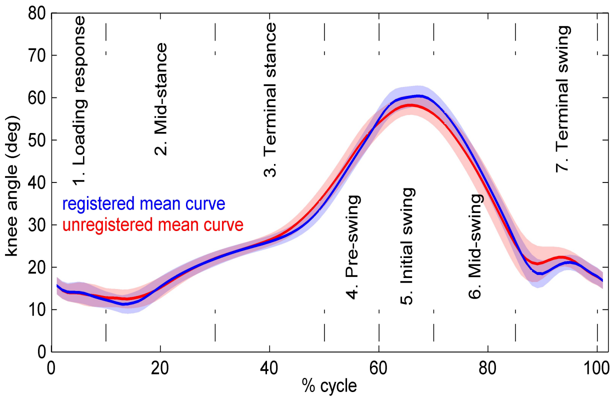


Fig. 3. Registered and unregistered mean curves of an injured subject.

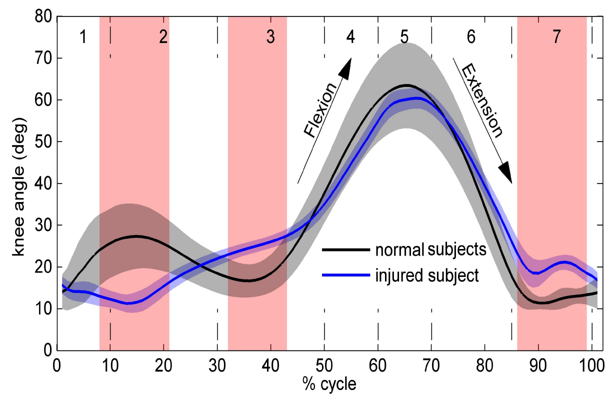


Fig. 4. Registered and unregistered mean curves of an injured subject in comparison to the overall registered mean of normal subjects. Phases of statistically significant differences are indicated by the vertical bands.

be seen in Table II, F-measures vary between 0.913 to 0.992. Walking and agility cut have the highest F-measures followed by jogging, sprinting, jumping on the box and football kicks.

### *C. Technique Evaluation*

In the simulated training intervention the subjects were asked to jog for one minute where about 30 foot contact cycles could be identified for each subject. It can be seen in Fig.3 and Fig.4 that the generated curves show the classic bimodal shape, with a small $(0 - 35\%$ cycle) and large $(35 - 90\%$ cycle) sequencing of flexion-extension. The statistical analysis indicated significant differences between the unregistered and the registered mean curves. The unregistered mean curve demonstrated significantly higher $(p = 0.002)$ and lower magnitudes $(p < 0.001)$, for $(32 - 58\%)$ and $(62 - 82\%)$ of the foot contact cycle, respectively. Differences are similarly evident at an intra-subject level.

It can be seen that in the first phase $(1 - 35\%)$ of the examined foot contact cycle the registered and unregistered curves are very similar (except for the magnitudes between $(10 - 20\%)$. However, for phases beyond $35\%$, both curves start to show differences in magnitude, timing characteristics and standard deviation. This is due to greater intra-subject variability beyond $35\%$ of the movement cycle, which affects the mean curve. By solely averaging the foot contact cycles (unregistered approach), the generated mean curve is altered by the intra- or/and inter-subject variability and can lose very valuable information about the subject. This can be extremely important in injury studies, where small differences from normal healthy subjects or small intra-subject differences over time may indicate a predisposition to injury or the early stages of injury; requiring the implementation of an appropriate training intervention. The more complicated or oscillating the collected biomechanical data, the more important it is likely to be to register the data.

It can be seen in Fig.4 that the runner with low back pain exhibited clear differences from the normative data, especially over phases $(8-21\%)$, $(33-41\%)$ and $(86-99\%)$. In normal subjects the knee generally flexes during initial loading $(0 - 10\%)$ and early mid stance $(10 - 15\%)$ while in the injured subject it clearly extends. The initial loading response involves the bi-articular hamstring muscle acting concentrically to extend the hip to keep the trunk upright, and as a consequence of the hamstring also being a knee flexor muscle, this results in knee flexion. Therefore, the abnormal knee extension in the injured subject appears to indicate either a compensatory or injury causing movement strategy indicative of the trunk inappropriately flexing during the initial loading response. From a compensatory perspective, this may be a strategy to reduce lower back impact loading with the trunk extensors acting eccentrically to cushion the action. Possibly in response to the abnormal early knee extension, knee flexion is initiated much earlier in the injured subject (at $15\%$ of the cycle) compared to normal $(at\ 35\%)$. The greater knee flexion in the injured subject during the terminal swing phase (85-100%) may be indicative of a crouched ("Groucho") running style aimed at reducing impact loads and hence reducing back pain and further injury [35].

## IV. Conclusion

In this paper, we described a novel body worn inertial sensor framework capable of automatically segmenting and classifying various actions in outdoor unconstrained environments, calculating extension-flexion knee angles that uses functional data analysis to both generate accurate normative data and compare individuals to this normative data. The proposed novel framework employed a Random forest training algorithm in conjunction with a DWT feature extraction technique to successfully classify training session activities with up to $98\%$ overall accuracy. Using the body-worn inertial sensors on the thigh and shank of a subject and applying the gradient descent based filter, the local orientation of each sensor was estimated and hence the extension-flexion knee angles were obtained. The calculated knee angles were input to a data analysis tool at the end of the pipeline to provide accurate movement technique assessment. In this approach it is necessary to register the trials before averaging them to ensure the true magnitude and shape of the data is preserved for both group and individual based data. If this is ensured, the presented framework has significant potential for monitoring athletes throughout training and competition to (a) identify injury and performance related determining factors, (b) identify individuals early in an injury pathway prior to extensive tissue damage, and (c) identify individuals predisposed to injury because of their movement technique.


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