# Object Tracking on Appearance-Based Modeled Soft-Irregularity Surfaces

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**Abstract.** The goal of this research is to develop autonomous robots capable to pursue an object and, at the same time, to adapt its speed depending on the surface's irregularities and textures. Besides, the robots must pursue the object by applying cooperative strategies for soccer games. The target object, surface irregularities and textures are appearance-based modelled.

**Keywords:** Appearance-Based Modelling, Texture Roughness, Cooperative Strategies.

## 1 Introduction

RoboCup's small-size robots move agile on the game field, but they are not designed to move on surfaces with irregularities, such as surfaces with different kind of textures, holes or slopes [6], [16]. Up to now, RoboCup tournament has not paid attention to surface features [7], [8]. A RoboCup's small-size game works as follows. There are two teams on a field; each team has five players which receive instructions from their respective "coach", via wireless. A digital video camera, located at two or three meters over the surface, sends game images, aerial view, to coaches. The coaches process the game images, then make decisions, attacking and defensive strategies, and finally communicate the instructions to their players. By adding surface features data, the players must move considering the irregularities, for instance, if surface is slippery, then the players must move slowly in order not to suffer slides, but without ignoring the coach's orders. Robotic soccer games involve high-difficult problems for pattern recognition, decision making and concurrency control. The problems to solve are, to identify the surfaces irregularities, textures, holes and slopes, to develop adaptive speed for players, to track objects in motion, ball and players, to avoid collisions between players and to build attacking and defensive strategies. Studying these problems will help to develop real world-approximated robotic soccer games, and robots capable to explore unknown terrains.

Navigation of autonomous vehicles and motion of robots have been of interest for space exploration [3], [9], navigation missions through unknown terrain [9], [10], [18] or collective games [4], [17], [22]. The collective game of robots playing football soccer implies to compete for both field game spaces and the ball. It must control the player's access to each part of the game field and the ball in order to avoid collisions; it can be achieved by applying concurrent programming techniques [2].

In [3] uses a vibration-based method for terrain classification for planet reconnaissance. Vibrations are measured using an accelerometer mounted on the robot structure. The classifier is trained using labeled vibration data during an offline learning phase. The algorithm uses signal processing techniques, principal component analysis and linear discriminant analysis. The algorithms of obstacle detection and local map building [9] are enough for cross-country navigation. In architecture based on behavior, these algorithms control the vehicle's speed considerably higher than a system that plans an optimal path through a high resolution terrain's map. In [18] presents a method that enables a vehicle to acquire roughness estimation so as to navigate at high velocities. It uses supervised self-learning, that enables the vehicle to learn to detect rough terrains while it is in motion and without human help. The training data is obtained from a filter analysis of inertial data acquired in the centre of the vehicle. Such data is used to train a classifier that predicts the terrain roughness from a laser ray. 3D textured surfaces recognition modeled via multiple histograms of micro-textons extracted with a multiresolution local binary pattern operator is proposed; for each image pixel, by thresholding its neighborhood with the value of the center pixel, a binary code is produced [15]. A histogram is created to collect up the ocurrences of different binary patterns. In [20] a machine vision system for roughness classification of cast surfaces is presented. The method of assessing surface quality is based on the two-dimensional Fourier tranform of a cast surface, in both gray-level image and binary image. The Bayes and neural network classifiers are implemented for texture classification according to the discriminant features derived in the spatial-frequency domain. In [17] describes LochNess, a hierarchical real-time control system for sensor networks. LochNess is applied to pursuit evasion games in which a group or evaders are tracked using sensor network and a group of pursuers are coordinated to capture the evaders. Although sensor networks provide global observability, they cannot provide high quality measurements in a timely manner due to packet loss, communication delay, and false detections.

## 2 Research Objectives

1) Appearance-Based Modeling of surface textures and slopes, 2) Robotic soccer players learning based on Neural Networks for moving and tracking on soft surfaces, less than 15 degrees of slope, 3) Concurrent pursue of moving object on soft-irregularity surfaces.

## 3 Methodology

It is necessary to identify the surface's irregularities [5], holes, slopes and textures [14], [20], in order to players move safely on irregular surfaces. We propose to appearance-based model such irregularities. This method computes the principal components from objects' image distribution [1], [11], [21]. For this case, images of holes, slopes and textures are taken from an aerial view. The principal components are used to train a neural network in order to classify the surface irregularities. Due to our video camera is located on top of the surface; it gives a surface aerial-view image. But, the surface features cannot be detected, because the whole image would be modeled as an only one object, therefore, the surface features would not be well integrated or even omitted. Thus, the surface is divided in squares, squaring, so as to get more information about surface features, and to identify such irregularities easily. Besides, squaring is employed as a reference system for players. The team is divided in five players and one "coach", both coach and players are modeled as autonomous agents [13], [17], [19], [22], because they can communicate between them and can modify and learn from their environment. The coach receives information from the video camera, elaborates strategies, makes decisions and sends its instructions, surface locations the players must occupy, to the players. Each player adapts its speed depending on the surface textures, computing the friction force generated by the textures [24], and decides where it can navigate in order to achieve a surface location. For ball tracking, the ball is also appearance-based modeled for a later recognition phase. Up to now, there are not appearance-based tracking methods. Usually motion is detected with optic flow methods, and then the object in motion is identified with appearance-based method [12], [23]. Because of the game's nature, it is possible that the ball suffer occlusions. In order to robust ball tracking, future-states estimation, Kalman filter, is contemplated for our work. In football soccer game, the players compete for the ball and positions on the field. So, it is necessary to implement a concurrency control (CC) mechanism so as to synchronize the players such that work cooperatively in order to complete strategies, and avoid both collisions between players and ball disputes between team partners.

## 4 Preliminary Results

Several simulations with robots walking on surfaces with different textures have been made. Simulations showed speed variations when a robot detects a texture change. When the texture roughness is small, the robot walks slowly. On the opposite, when the texture roughness is huge the robot moves faster. We mean that if the texture roughness is small the surface is slippery, e.g. ice track, and so the robot cannot do abrupt moves, then the robots' speed cannot be high. For huge texture roughness, e.g. a grass field, the robot can move fast and stop quickly without slides. In football soccer simulations the team with the ball looks for an advantage position in order to make a goal, avoiding the rival's mark. Each defender pursues an attacking player previously assigned. The coach of the attacking team indicates each player which part of the field has to move. The opponent's coach locates the position of each attacking player and notifies to its players the current location of attacking players. Although each coach is a monitor of the player's movements, they do not notice the collision risk between them. Each player locks and releases the squares necessary to complete its trajectory. Before a player walks, the player verifies if the square, where is going to move, is occupied; if it is not occupied, the players locks the square and then it occupies it. When a square is locked, no one else can move to that square until the owner decides to move and then releases the square when the player has already left it. If the square is occupied, the player must round it, if it is possible, or wait for new instructions from the coach. From simulations of two teams with five players per team, it concludes that the CC proposed is successful by avoiding collisions between players, for surfaces totally plain and smooth.

The current state of the research consists on simulations. It is planned to make practical implementations with the Bioloid Robotis Kit. At this moment both object tracking method and cooperative strategies are being defined. The tracking methods that have been considered are tracking using template and density-based appearance models and tracking using multiple objects [23].

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