Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

División de Estudios de Posgrado

Natural hand-gesture interaction

(Interacción natural con gestos manuales)

por

David Juvencio Rios Soria

en opción al grado de

Doctor en Ingeniería

con acentuación en Computación y Mecatrónica

San Nicolás de los Garza, Nuevo León junio 2013

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Los miembros del Comité de Tesis recomendamos que la Tesis ≪Natural hand-gesture interaction≫(Interacción natural con gestos manuales), realizada por el alumno David Juvencio Rios Soria, con número de matrícula 1213374, sea aceptada para su defensa como opción al grado de Doctor en Ingeniería con acentuación en Computación y Mecatrónica.

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San Nicolás de los Garza, Nuevo León, junio 2013

Resumen

David Juvencio Rios Soria.

Candidato para el grado de Doctor en Ingeniería con acentuación en Computación y Mecatrónica

Universidad Autónoma de Nuevo León.
Facultad de Ingeniería Mecánica y Eléctrica.

Título del estudio:

Interacción natural con gestos manuales

Número de páginas: 108.

Objetivos y método de estudio: El objetivo de este trabajo es realizar un estudio acerca de los diferentes métodos de interacción humano-computadora basados en gestos manuales y proponer un sistema que sea fácil de utilizar y pueda ser usado en diferentes aplicaciones. Para este trabajo se realizó un estudio de los sistemas actuales de interacción humano-computadora, así como de los fundamentos cognitivos y de diseño en los cuales debe de estar basado el desarrollo de este tipo de sistemas.

Uno de los propósitos de este trabajo es la creación de un sistema de reconocimiento de gestos manuales; para el desarrollo de este sistema se hizo un estudio acerca de técnicas de visión computacional. Para comprobar el correcto funcionamiento del sistema se llevaron a cabo experimentos con usuarios reales.

Contribuciones y conclusiones: Se creó un algoritmo de reconocimiento de gestos manuales basado en técnicas de visión computacional; este sistema es capaz de detectar seis diferentes señas manuales en tiempo real. Estas señas se podrían usar en secuencia para crear así un vocabulario más ámplio usando diferentes combinaciones de éstas.

El sistema se puede implementar fácilmente utilizando una cámara web y puede ser adaptado para ser usado en diferentes aplicaciones. Se crearon algunas pruebas de conceptos que demuestran como se puede utilizar este sistema para controlar distintos dispositivos electrónicos. Se realizaron experimentos con usuarios utilizando este sistema obteniendo una precisión del 93% en el reconocimiento de gestos, requiriendo 270 milisegundos en promedio para el tiempo de ejecución.

Firma del asesor: ______________________________

Dra. Satu Elisa Schaeffer

Abstract

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Candidate for the degree of Doctor of Engineering in Computation and Mechatronics

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Facultad de Ingeniería Mecánica y Eléctrica.

Study title:

Natural hand-gesture interaction

Number of pages: 108.

Objectives and methodology: The objective of this work is to study the different methods of human-computer interaction based on hand-gestures and propose a system that is easy to use and can be used in different applications. We conducted a literature review of current work in human-computer interaction as well as the cognitive and design foundations on which the development of such systems should be based.

The main purpose of this work is to create a hand-gesture recognition system. For the development of this system, we applied computer-vision techniques. To verify the correct operation of the system, experiments were carried out with real users.

Contributions and conclusions: A hand-gesture recognition algorithm was created based on computer-vision techniques; this system is able to recognize six different hand signals in real time. These signs could be used in a sequence to create a bigger vocabulary using different combinations of the signs.

The system can be easily implemented using a webcam and can be adapted for use in different applications. Some conceptual prototypes were created to demonstrate how this system can be used to control various electronic devices. Experiments were conducted with real users interacting with the system, obtaining an accuracy of 93 % in gesture recognition, using 270 milliseconds average for processing time.

Signature of advisor: ______________________

Dra. Satu Elisa Schaeffer

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Nomenclature

3D	Three-Dimensional Space
3G	3rd Generation
AR	Augmented Reality
CRT	Cathode Ray Tube
CV	Computer Vision
DG	Differential Gradient
GB	Giga Byte
GPS	Global Positioning System
GSM	Groupe Special Mobile
HCI	Human-Computer Interaction
HTTP	Hypertext Transfer Protocol
IR	Infrared
IrDA	Infrared Data Association
IT	Information Technologies
LAN	Local Area Network
LBC	Location Based Computing

MHz	Mega Hertz
MP	Mega Pixel
P2P	Peer to Peer
PC	Personal Computer
PDA	Personal Data Assistant
RAM	Random Access Memory
RFID	Radio Frequency Identification
RGB	Red Green Blue
SMS	Short Message Service
SSA	Shared Situation Awareness
TM	Template Matching
VE	Virtual Environment

Chapter 1

Introduction

Currently, numerous new mobile computing systems are being developed thanks to the emergence of technologies such as GSM, GPS, and RFID. In this chapter, we discuss some representative examples of mobile computing applications that make use of emergent technologies: location-based systems, mobile assistance systems, emergency response systems, collaboration systems, and mobile context-aware systems. We also introduce *augmented reality* as well as how interact with such systems. Also, examples of how augmented reality systems and mobile computing systems are being combined to create new technological solutions are discussed. Finally, with the concepts introduced in the chapter, we provide the motivation for the research carried out in this thesis.

1.1 Mobile Computing

Mobile computing is human-computer interaction by which a computer is expected to be transported during normal usage. Mobile computing involves mobile communication, mobile hardware, and mobile software. Mobile computing is “taking a computer and all necessary files and software out into the field” [15, 21].

1.2 Distributed Computing

A distributed computer system consists of multiple software components that are on multiple computers, but run as a single system. The computers that are in a distributed system can be physically close together and connected by a local network, or they can be geographically distant and connected by a wide area network. A distributed system can consist of any number of possible configurations, such as mainframes, personal computers, workstations, minicomputers, and so on. The goal of distributed computing is to make such a network work as a single computer [24].

1.3 Mobile Distributed Computing

DreamTeam [48] is a framework for distributed applications. DreamTeam focuses on two problems: temporary disconnections and high latency. It reduces development costs by re-using code. The ambient is divided into mobile and stationary part. There is a session handler that starts and stops the session and allows to enter and leave the sessions. It uses a remote *proxy*[1] to perform heavy tasks and store data when the mobile device is disconnected. Pocket DreamTeam, also proposed by Roth et al. [48], was implemented and tested using PDA's, workstations, and wireless LAN. Two applications were selected for the mobility extension: a diagram tool and a drawing tool.

MaGMA (Mobility and Group Manager Architecture) [35] allows the use of real-time collaborative applications, such as *Push-to-Talk*. MaGMA is an architecture for managing mobile networking groups connected via internet that uses distributed servers for scalability both in the number of groups and the number of group members. It supports geographically scattered groups efficiently and reduces traffic.

[1] A proxy is a server, a computer system, or an application that acts as an intermediary for requests from clients seeking resources from other servers.

1.4 Ubiquitous Computing

Ubiquitous computing is the integration of information technologies in everyday life in such way that a computer is viewed as an environment. The goal is to insert computer components to naturally interact with people and their daily activities. As proposed by Weiser [70], in an ubiquitous-computing scenario, hundreds of computers may be interacting with a person at a specific location such as home or office; these computers should blend with the environment in such a way as to be invisible, discreet, and give the feeling of being part of a natural environment.

A user on a personal computer or laptop consciously interacts with a system; the user can interact with the system in various ways, but always directs attention — at least partially — on the device. In ubiquitous computing, there are no users per se; there are individuals who are exposed to the system. Ubiquitous systems interact with users without requiring attention and without affecting the routine [71].

An early stage of ubiquitous computing is *mobile computing*. It involves mobile computing devices and systems that go beyond the desktop and allow remote access. Mobile computing arises from the development of cellular networks and low-cost devices. This is compounded by the presence and increasingly common use of location systems based on geographical positioning (GPS). Thanks to these elements, mobile computing scenarios are created, with forms of communication and collaboration that were previously impractical.

Within mobile computing, many different applications arise, such as *location-based systems*, *emergency response systems*, *mobile collaboration systems*, and *context-aware systems*. Each of these areas will be discussed individually below.

1.4.1 Location-Based Computing

Computer systems based on location can be used for different applications such as roadside assistance [49]. For example, VANET [49] is a platform for ad-hoc vehicular networks; such networks form part of a "smart" road. In a smart highway, vehicles send and receive notifications of road conditions, such as traffic jams. Vehicles can also change their status if they suffer damage. The system is monitored by an operator and can also be accessed online to consult conditions beforehand.

Another example of such systems is OneBusAway [20] that is a suite of tools that provides real-time information about public transport routes. Making use of the mobile device, location information is transmitted to and displayed on nearby bus stops. Also a transportation schedule is shown on the bus stops for the users to see whether or not the busses are on time. This allows the users to better plan their trips.

1.4.2 Mobile Assistance

An example of mobile assistance systems is Smart Food [25]: a support system for mobile in-place warnings for specific products in a supermarket. Applications for such systems include notifications about allergies or products under a dietary or economic restriction, based on combining user preferences with the product details. The proposed implementation consists in adding a barcode reader to a PDA: the product's barcode is scanned at a supermarket, the information is sent via SMS or HTTP to a consultation service, which in turn returns the information of the product as a reply. The information received as reply is then automatically compared with the user profile to provide a personal response on the user interface on the PDA. Manufacturers and retailers can gain competitive advantage by offering a mobile query system; it can be seen as a bidirectional communication system that brings the customer and the producer closer.

Another example of an assistance system is SAMU [14], a mobile emergency-care system. It makes use of multiparameter monitors, videos of the patient, ultrasound, and 3G (3rd generation) technology to send data from a pre-hospital ambulance to the database at a hospital to improve patient care. An assistance network of this kind was implemented for the transmission of vital data in real time, to train equipment for mobile units, and to develop evaluation methods.

1.4.3 Emergency-Response Systems

Fröhlich et al. [23] explore the potential of *spatial interaction* with mobile emergency-response technologies. They discuss a scenario where a fire occurs in a stadium and people use their mobile devices to trace a 3D (three-dimensional) representation of the area, to find the emergency exits, and to mark the ones that are blocked. The gathered information is transmitted to the rescue corps that use the 3D map constructed from the traces in order to obtain a more accurate description of the situation.

Sapateiro et al. [50] propose a model for mobile collaborative activities in crisis scenarios or emergencies. *Shared situation awareness* (SSA) is implemented on devices such as tablets and PDAs using two-dimensional arrays storing information regarding the situation and the location of each user. An experiment was conducted with teams of IT service of different organizations. The prototype operates on tablets and PDA's that connect among the devices into a P2P system, the application finds partners and establishes a reliable link to transmit data.

Sapateiro et al. [58] have also developed support systems for fire detection; they propose a tool for decision making in a mobile device that helps supervisors in the emergency-response center. It was developed for use on PDAs in emergency situations, both in real time upon an emergency and during routine inspections. It has its own database that is monitored to make the right decisions. To evaluate the usability, experiments were conducted with twenty students: half use the system and the other half employ traditional methods. The research team assessed the training time, the time for safety inspections, and the frequency of errors. The user group that had the PDAs spend less time managing the response to emergencies; however, they spent significantly more time on inspections that the traditional group. Using the system, supervisors could quickly understand the situation and fully control it quickly. It can also be used for training rookies.

1.4.4 Mobile Collaboration

Mobile computing systems also allow the development of collaborative applications, where the users collaborating in the system can either access it from a stationary computer or from a mobile device. Messeguer et al. [41] made an experimental study of how ad-hoc networks can support mobile work collaboration. Several scenarios were considered for experimentation: one with purely static users, another with one mobile user while all others were stationary, and different configurations of subgroups. For the experiment they used eight laptops and employed different metrics to measure the quality of connections and traffic generated. Messeguer et al. provide recommendations for designing applications in this type of infrastructure.

Joyce [43] is a software tool to program collaborative and dynamic mobile applications. Joyce provides a model for such applications and the implementation of the principles described in this model.

According to Ochoa [44], typical requirements for and elements of mobile collaborative work include the type of mobility, the duration of the activity, group structure, power supply, interoperability, and robustness.

1.4.5 Context-Aware Systems

Context-aware systems interact depending on the data they get from their environment. For example, CONjurER [51] is a mechanism to store and retrieve information in context. In a test scenario, Schirmer et al. implement an *environmentally sensitive* *switch* for controlling the volume and the channel of a television using information from a tracking system that follows using ActiveBadge[2] the location and movements of members of staff in a laboratory.

In context-aware applications, the interaction can be interpreted based on physical location, time period, context of activities, et cetera. An example is a situation-dependent chat proposed by Hewagamage et al. [28] that allows people in a particular context to collaborate with each other without exposing their personal identities: when a user enters an active area, the system automatically connects to a corresponding chat channel, and the disconnects automatically when the user exits the area.

The ePH system [65] is an infrastructure to build a dynamic community that shares information and knowledge about sites of interest that are accessible through context-aware services. Content includes information from public places of interest such as pharmacies, hospitals, gas stations, entertainment venues, restaurants, hotels, et cetera.

DealFinder [10] is a prototype of a shopping assistant that is aware of the position for mobile devices. It allows consumers to make more informed decisions about the products they buy. It allows asynchronous sharing of information about prices and product availability.

1.5 Methods for Estimating Location

In order for location-based systems to function properly, it is necessary to determine the location of the user, either indoors or outdoors, to an adequate precision. There are various tools available for this purpose, such as the Global Positioning System (GPS), GSM, Radio Frequency ID, et cetera.

[2] An ActiveBadge emits a unique code for approximately a tenth of a second every 15 seconds (a beacon). These periodic signals are picked up by a network of sensors placed around the host building.

1.5.1 Global Positioning System

The *Global Positioning System* (GPS) is used to determine a device's geographical position in terms of latitude, longitude, and altitude. It is based on a constellation of 21 satellites orbiting the earth at an altitude of 20,200 km, requiring 11 hours 58 minutes to describe a complete orbit [17]. The system that communicates with the satellite to determine its position is a GPS receiver: it measures the distance from each satellite to the receiver antenna. The satellites send radio waves to 300,000 km per second and the transmission delay is used to infer the distance. Calculating the distance to any four satellites can determine the position of the receiver device. Satview [54] is a visualization tool that shows in real time GPS availability. It uses a three-dimensional model of the environment and the position of the satellites to calculate the shadows of coverage.

1.5.2 Radio Frequency Identification

Radio Frequency Identification (RFID) is a system of storing and remotely retrieving data using devices called RFID tags, cards, or transponders [8]. The fundamental purpose of RFID technology is to transmit the identity of an object (like a unique serial number) via radio waves.

RFID tags are small devices that can be attached or incorporated into a product, an animal or person. These tags contain antennas to enable them to receive and respond to requests by short-range radio from an RFID transmitter-receiver. Passive tags require no internal electrical power supply, while the active typically employ batteries. One of the advantages of using radio frequency (rather than, for example, infrared[3] is that a line of sight between sender and receiver is not necessary.

[3] IR data transmission is employed in short-range communication among computer peripherals and personal digital assistants. Remote controls and IrDA (Infrared Data Association) devices use infrared light-emitting diodes (LEDs) to emit infrared radiation which is focused into a narrow beam. The beam is modulated to encode the data. The receiver uses photodiode to convert the infrared radiation to an electric current. Infrared communications are useful for indoor use.

Want et al. [69] implement one of the first applications of radio frequency tags: a system to determine the location of employees within an office.

The MyGROCER system [32] for supermarket shopping makes use of RFID tags on each product to identify the items as they are added to the cart. The shopping cart has a screen that indicates the items that are yet to find based on a shopping list defined by the user. When the user finishes shopping, it is not necessary to pass the items by the cash register, as the cart automatically transmits to the cashier the listing of the items it carries upon arriving to the register.

1.5.3 Special Mobile Group

GSM stands for "Special Mobile Group" (in French); it is a standard for communication via mobile phones that incorporate digital technology[4]. Due to being digital, any GSM client can connect their phone through their computer and can send and receive messages by e-mail, faxes, surf the Internet, access to a company network well as use other functions of digital data transmission, including *Short Message Service* (SMS), commonly known as *text messages*. Antennas using GSM can determine the location of a mobile device connected to the system comparing signal strengths among three or more antennas, similar to the computation used in GPS, although less precise [6].

1.5.4 Orientation Sensors

Orientation sensors built into mobile devices enable new services and applications. Using three-dimensional terrain models and mobile phones one can access as pointers to information of an area of interest by pointing the device in a real-world direction [53], enabling the user to retrieve information without even knowing the name of point of interest. A prototype was built by adding a three-axis compass to a

Infrared does not penetrate walls and so does not interfere with other devices.

[4] `http://www.gsma.com/`

mobile phone; presently several mobile phone models include a compass as well as orientation sensors.

1.6 Information Visualization

The problem to represent information on mobile devices is the low resolution of many of the displays, an even those that have high resolution, are small in size in order to be comfortably mobile. Yee et al. [75] propose to deal with the problems of small screens on mobile devices with Peephole Displays that only show a part of the information at a time in a naturally navigable manner.

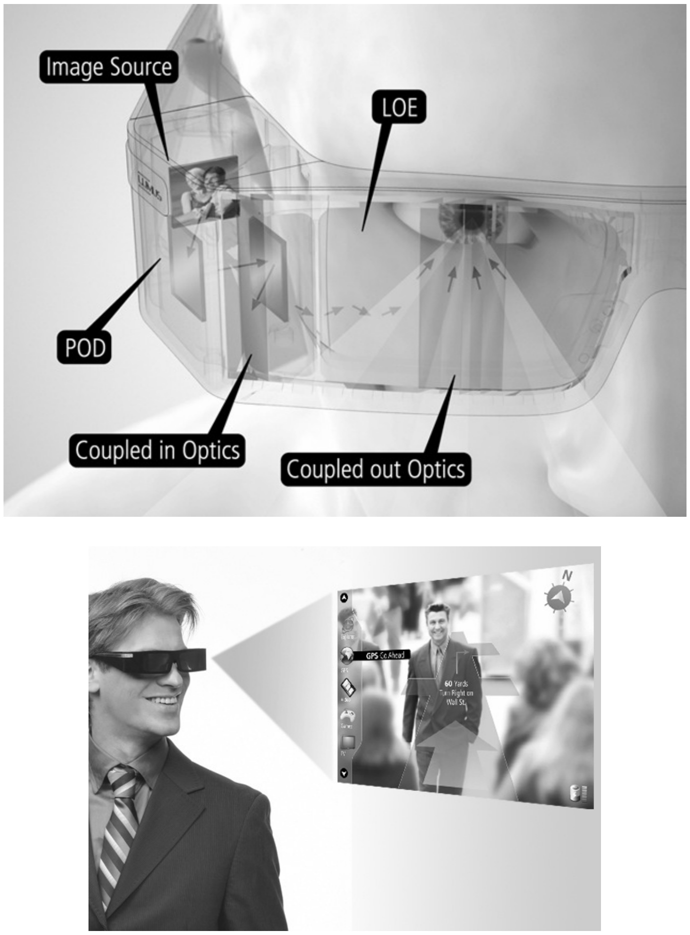


Figure 1.1 – The LUMUS personal display[5].

[5] http://www.lumus-optical.com

In events like exhibitions and fairs where there are different places of interest distributed over a large area, a user attempting to visualize the information on the products and services available faces an overwhelming amount of data. It is crucial to provide adequate and relevant information in a comprehensible manner that permits good spatial perception [5].

Several companies and research laboratories have spent years developing new ways to represent information to extend the user experience beyond the screens of mobile devices: micro-projectors have been created to visualize information directly on the windshield of the car, for example, or personal glasses (cf. Figure 1.1). This brings us to the field of *augmented reality*, discussed in the next section.

1.7 Augmented Reality

Augmented reality (AR) is a term used to define a direct or indirect vision of a real-world physical environment, combined with virtual elements, thus creating a real-time mixed reality [4]. Augmented reality consists in generating virtual images incorporated on the field of vision of the user. With the help of technology (typically computer vision and pattern recognition), information about the real world around the user becomes interactive and digital.

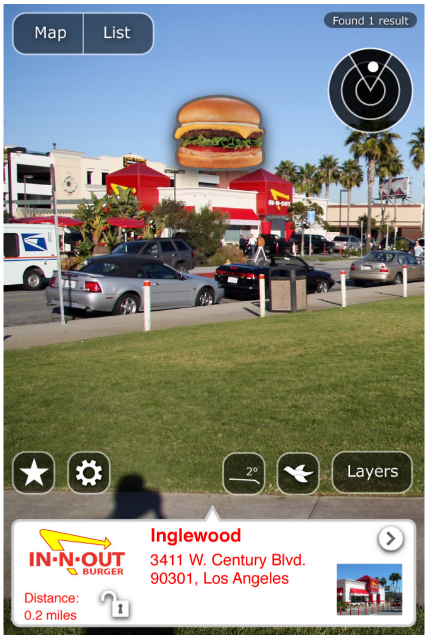
The field of application for augmented-reality systems is immense: it is used in medicine (surgery), museums (reconstructions of archaeological remains), training (flight simulators, surgical interventions), in military applications (location maps, geolocation), and is increasingly being used more in advertising and marketing [4].

Currently there are commercial augmented-reality applications for mobile devices that display information about places of interest such as nearby restaurants, museums, et cetera (cf. Figure 1.2). Foursquare[6] and Gowalla[7] [18] introduce as-

[6] `http://www.foursquare.com`

[7] Gowalla was a location-based social network launched in 2007 and closed in 2012. Users were able to check in at “Spots” in their local vicinity, either through a dedicated mobile application or

pects of games to social networking applications based on location: a user can find friends nearby and decide to go see them. The users collect badges or points for the different places they visit and collect virtual objects, which encourages people to explore the cities where they live. These software tools work with GPS devices and compasses to determine the position and orientation. With the location information, the tool then searches for relevant results that it then displays as an image overlay on live camera. Some systems such as Urbanspoon[8] allow for corrections to the position by moving a cursor on the map.



Inglewood
3411 W. Century Blvd.
90301, Los Angeles

Distance:
0.2 miles

Figure 1.2 – The Layar augmented reality application[9].

ARToolKit[10] is a library that allows the creation of augmented-reality software in which virtual images are superimposed on the real world. It uses the video tracking, calculated in real time, and records the camera position and orientation relative to the position of specific physical markers. Once the real camera position is known, 3D models can be placed exactly on the marker overlapping the actual

through the mobile website. Checking-in would sometimes produce virtual "items" for the user, some of which were developed to be promotional tools for the game's partners.

[8] `http://www.urbanspoon.com`

[9] `http://www.layar.com/`

[10] `http://www.hitl.washington.edu/artoolkit`

object. Thus ARToolKit solves two major problems in augmented reality, tracking the view and viewing virtual objects.

1.8 Virtual Object Interaction

Being able to see virtual objects raises the question of how to interact which such objects. The interaction with virtual objects is challenging; often interaction is performed using physical devices as trackballs or placing markers on the hands or wearing special gloves. Kölsch proposes the HandVu [31] system of hand signals, recognized with computer-vision techniques. The system allows the user to interact with virtual objects (cf. Figure 1.3); the signs used are easy to understand, but nevertheless not natural gestures. This are not natural gestures in the sense that are gestures not commonly used by a person in a daily basis, but can be learned.

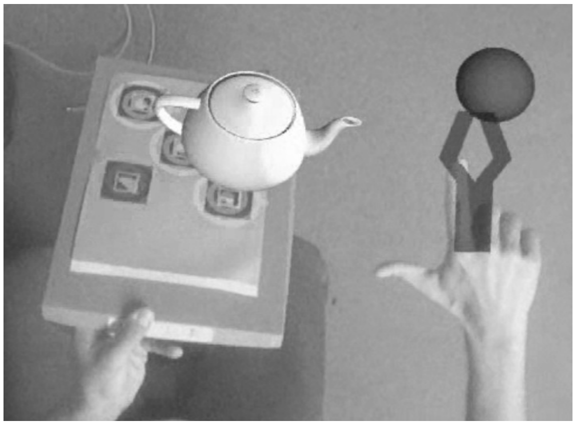


Figure 1.3 – Handvu virtual object interaction[11].

The *interactive display* developed by the agency The Alternative in the UK is the window in a department store that allows touch-free interaction using only the hands moving them in front of the screen. In the Electronic Entertainment Expo 2009, Microsoft presented the project Natal Xbox 360 (released commercially as Kinect[12] in 2010); this game and entertainment system allows play games and

[11] http://www.movesinstitute.org/~kolsch/HandVu/HandVu.html

[12] http://www.xbox.com/en-US/KINECT

interact with the system using voice commands and recognition of body movements that are captured by infrared sensors.

1.9 Digital Advertising

Advertising is one of the present-day major ubiquitous computing applications [34]. Currently there are several mobile advertising systems, such as buses or taxis which change the advertising on their screens depending on the area of the city through which they pass (cf. Figure 1.4). Advertisers that detect the radio station tuned in the radios circulating around to show appropriate messages. Other companies have equipped advertisements with cameras to determine the age and gender of the viewers and then display the advertisement accordingly.

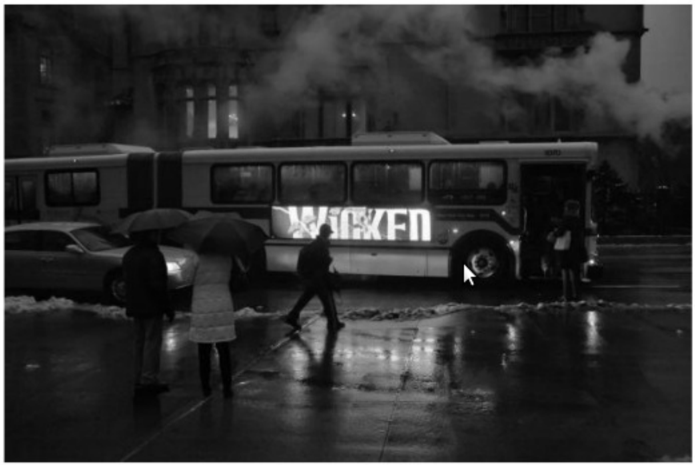


Figure 1.4 – Digital advertising on a bus that changes depending on the location and the time of day. (Taken from [34].)

The main problems of digital advertising are the selection of potential clients, the evaluation of the effectiveness of advertising, and ensuring customer privacy. Even so, with the combination of elements of mobile computers, tracking systems, and augmented reality, digital advertising is now possible in scenarios that were previously impractical.

Take a person who makes purchases in a shopping center. Suppose that the person wants to know where the music store is, and so performs a search on their smart phone to find out where the store is located. The screen of the smart phone shows a map of the shopping center, highlighting the location of the store, while at the same time augmented-reality glasses worn by the user indicate the path to follow to get there from the current position. While walking through the plaza, the augmented-reality vision highlights the stores that have products on sale that are marked on the users shopping list.

When entering the music store, the user receives on the smart phone coupons and promotions. While spending time in the store, the user receives product suggestions based on previous purchases, as well as recommendations for products acquired by people in their social network. When finished shopping, the smart phone indicates the mall exit closest to where the user parked the car, again shown both on map on the device and in an augmented-reality view.

The user has an enhanced shopping experience, and by combining the augmented-reality glasses with the smart phone, can explore the inside of the mall in a more natural way than it would using simply the smart phone's screen, which would require more of the user's attention.

In the use case described above, it is also necessary to have an indoor location systems to determine with accuracy the location of the user within the shopping mall; by accurately determining the user location, the systems can filter the available information to display only the relevant information and thus not over-saturate the user with information that is unnecessary at the time.

1.10 Motivation of the Thesis

Currently there are already some commercial applications of augmented reality for mobile devices. However, these applications may well be compared to a mobile

Google Maps[13]: they typically display more information than we can see without using the system, but there is rarely a possibility to interact adequately with the virtual reality added to the field of vision. The way in which the information is shown is often through screens of handheld devices and the interaction is carried out using touch screens or keyboards. Most of the personal-vision systems that currently exist — such as lenses and headsets — also use keyboards or trackballs to interact with the system. Moreover, most existing systems that allow natural interaction with virtual objects are not mobile systems, but rather stationary and specific to a limited area of interaction such as the interactive screens and the Microsoft Xbox system using Kinect.

The users who interact with computer systems face different types of interaction such as keyboards, mice, trackballs, and monitors. Recognition of gestures allows to interact with a device free of touch, and if the gestures are natural, with very small cognitive load as little or no learning is required in the ideal case.

There are currently no systems that combine augmented reality systems on mobile devices with a natural interaction through hand-based gesture recognition [36]. One problem for the integration of such systems is the computational capability of the devices, since the mobile device must be able to handle virtual objects that are manipulated while performing the gesture recognition to interact with the system. This is becoming increasingly feasible with the increment in processor speed and the available memory in smart phones, as well as the higher-resolution screens and cameras, not to ignore the promise of widely commercializable personal displays of Google Glass[14].

In this work, we study new forms of natural user interaction with a augmented-reality environment in real time, without the user having to consciously direct attention to the computational device with which the interaction takes place. We also emphasize the importance of conducting a *usability study* of the proposed system to

[13] `https://maps.google.com/`

[14] `http://www.google.com/glass/start/`

examine the acceptance of users to this kind of technology.

1.11 Thesis Structure

As we are focused on design a new interaction device, it is needed foundations on how humans perceives and react; in Chapter 2, the fundamentals of cognitive science, principles and examples on human-computer interaction, and hand-gesture interaction are presented. In the same chapter the computer-vision basics and related work is discussed. In Chapter 3 our algorithm for hand-gesture recognition is presented, and in Chapter 4 a prototype for implementing such an algorithm. The experiments for testing the algorithm performance and the results are presented in Chapter 5. In Chapter 6 proofs of concept using the algorithm for hand-gesture recognition are presented, and in Chapter 7 our conclusions and proposals for possible future work are given.

1.12 Publication

Part of this thesis work was presented with the title “A Tool for Hand-Sign Recognition” [46] at the Mexican Congress on Pattern Recognition (MCPR 2012) held in Huatulco, Mexico. Proceedings of the conference were published in the Lecture Notes in Computer Science series by Springer.

Chapter 2

Background

As the thesis is focused on designing and implementing an interaction mechanism, a foundation of how a human being perceives, reacts, and understands is of essence. *Cognitive science* approaches the study of mind and intelligence from an interdisciplinary perspective, working at the intersection of philosophy, psychology, artificial intelligence, neuroscience, linguistics, and anthropology [61].

In this chapter we present the basic concepts about cognitive science, relevant in the development of new systems.

2.1 Perception

The perceptions is a sensory conscious experience. It occurs when electrical signals that represent an object in the brain, somehow transform the experience of seeing the object [26].

Recognition is the ability to locate objects that give them a level of meaningful status. The process of perception is a sequence of processes that work together to determine the experience of and reaction to stimuli in the environment. The steps in this process are the following:

- Environmental stimulus: Stimulus refers to what is out there in the environment, what one actually pays attention to, and what stimulates the receptors. The environmental stimulus is all of the things in the environment that one can potentially perceives.

- Attended stimulus: When a person focuses on an object, making it the center of her attention, it becomes the attended stimulus. The attended stimulus changes from moment to moment.
- Transduction: Transduction is the transformation of one form of energy into another form of energy.
- Neural processing: As electrical signals are transmitted through someone's retina and then to the brain, they undergo neural processing, which involves interactions between neurons.
- Perception: Perception is conscious sensory experience. It occurs when the electrical signals that represent an object are transformed by someone's brain into their experience of seeing the object.
- Recognition: Recognition is the ability to place an object in a category.
- Action: Action includes motor activities such as moving the head or eyes and locomoting through the environment.
- Effects of knowledge: Knowledge is any information that the perceiver brings to a situation.

The psychophysical approach of the perception focuses on the relationship between the physical properties of the stimuli and perceptual responses.

The methods used to study the perception psychophysical level are:

- Phenomenological method: The person describes what is perceived.
- Recognition: A stimulus placed in a category.
- Detection: Measurement of the thresholds. The absolute threshold is the minimum amount of energy needed to detect a stimulus, the difference threshold is the smallest difference between two stimuli that are detected.

- Estimated magnitudes: Indicate the qualities of brilliance and volume stimuli.
- Search: Measuring reaction time to find an other stimulus entity.

Light: The Stimulus for Vision

Seeing involves the stimulus and a mechanism that reacts with the light. The visible light is an energy band within the electromagnetic spectrum that humans can perceive. Visible light has wavelength ranging from about 400 to 700 nanometers.

The visual process starts once light is reflected from an object into the eye and is focused onto the retina and the lens forming the image object.

Perception Plasticity

The plasticity is the way in which the stimulus change and mold the perceptual system. The idea is that the structure and the way the visual system works (or any other sensorial system) can be mold by experience.

Hebb [27] suggested that repeated experiences, cause the same groups of neurons to fire this shot and strengthens the synaptic connections between neurons. Learning creates cell gatherings, which are more likely to trigger to a learned stimulus.

Visual Attention

Attention is the process of finding stimuli and subsequent concentration in them. It is important because it directs the receivers to stimuli that one perceives and also because it influences the information processing once it stimulates receptors.

Attention can strengthen the perception of stimuli one is focused on and reduce the awareness of stimuli one ignores. When a person focuses their attention on something of interest, he or she becomes more aware of what he or she is watching and less aware of objects or parts of the scene.

Object Perception

The ability to mental organization helps people establish perceptual arrangements. Gestalt laws [26] of perceptual organization are rules that specify how one organizes small stimuli into a whole.

- Law of proximity: It occurs when the parts of a whole receive the same stimulus, groups are formed in the direction of the minimum distance occurs automatically.

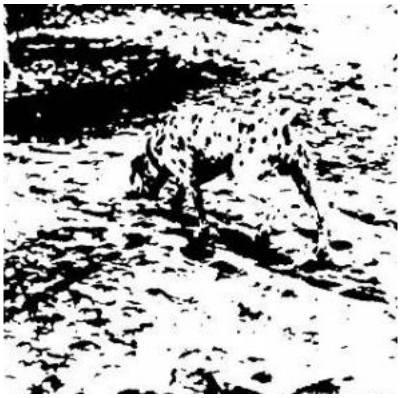


Figure 2.1 – Law of proximity example. (Taken from [26].)

In the picture there are a number of scattered points, once one recognizes in them a Dalmatian because one cannot stop seeing it. Previous experience (in the perception of that form as “Dalmatian dog”) acts potently on conscious awareness.

- Equality or equivalence act: When a person observe several different kinds of items, he or she tends to perceive that are equal objects form groups. This group will depend on the shapes and colors of the elements (most of the time the color has more weight than the forms).

- Law of good form and common destiny: This helps us to capture the essence of the forms presented. It allows easy reading of the figures due to different factors such as destination, synthesis, order, simplicity, et cetera.

- Law of enclosure: This is achieved when the receiver the associate the limit of a surface or shape to form a contour that does not actually exist.

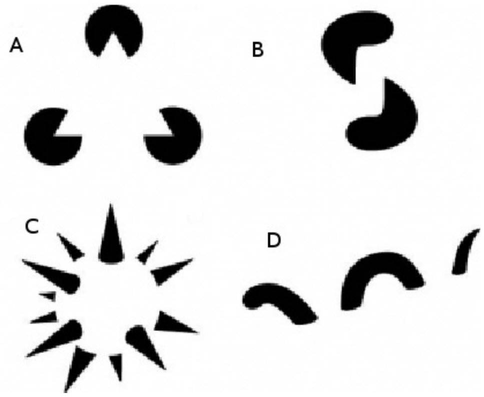


Figure 2.2 – Examples of enclosure. The viewer associate the limit of a surface or shape to form a contour that does not actually exist. In A) and B) the shapes form a triangle and a sphere. In C) and D) the shapes give the impression of continuity. (Taken from [26].)

- Law of experience: Individual human experiences shape perceptions of things.
- Law of symmetry: This law is generated from the balance, giving life to objects with minor modifications and alterations. Tridimensional shapes are achieved when figures are asymmetric, and on the other hand, are flat when they are symmetrical.
- Continuity law: This law is about how forms are represented. When the forms are shown in an incomplete or incomplete way so as to achieve an easy interpretation. The viewer is in charge of defining continuity of forms.
- Figure-ground law: Plane figures are presented on a background, creating depth perception. It defines what is perceived as a background figure, and

vice versa. It helps differentiate between the background and shape for easy perception.

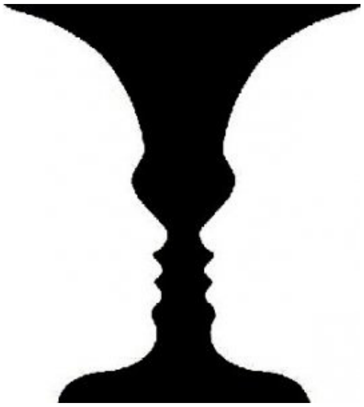


Figure 2.3 – Plane figures are presented on a background; perceiving the white as background one can see a vase; if the color black is the background, two faces can be seen. (Taken from [26].)

Color Perception

The color fulfills the function of highlight and facilitates perceptual organization. One can describe all the colors one see using the terms: red, yellow, green, blue, and their combinations. The order of the four basic colors in the color circle (cf. Figure 2.4) corresponds to the order of colors in the visible spectrum: at the end of the shorter wavelength is the color blue, green in the half, red and yellow at the end of long longwave.

Although the color circle is based on four colors, people can distinguish about 200 different colors throughout the visible spectrum. One may also create other colors by changing the intensity so that more bright or dim, or adding white, which contains equal amounts of all wave longitudes to change the color saturation. Changing the wavelength, intensity, and saturation, it is possible create around a million different discriminable colors.

The experience of color, as all sensory experiences, is created by the nervous system. The information on which wavelengths are reflected in the object is encoded

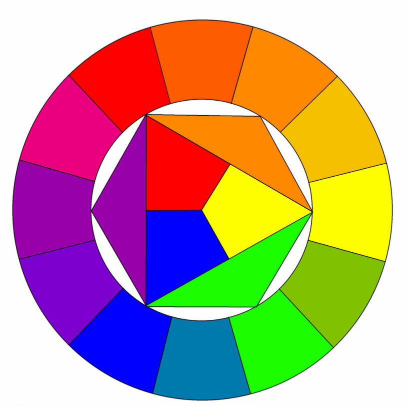


Figure 2.4 – Color wheel.

into neural impulses, which are then transformed into the experience of color. Color is the way in which the brain knows which wavelengths are present.

The color constancy refers to the way in which perception of color remains constant even when objects are viewed under different illuminations. The constancy of brightness refers to the way in which perception remains relatively constant when objects are viewed in different lighting conditions.

Depth Perception

The key theory of perception is concerned with identifying information of the image that corresponds to the depth of the scenes. If an object covers part of another, the object must be partially covered a greater distance than that covering it. This situation called occlusion is a sign or clue that an object is in front of another. According to the theory of the keys, one learns the relationship between this key and depth through the experience and environment. Once learned, the association between the keys and the depth becomes automatic. These cues can be divided into three major groups:

1. Oculomotor. Cues based on the ability to sense the position of the eyes and the tension in the eye muscles.

2. Monocular. Cues that work with one eye.

3. Binocular. Cues that depend on two eyes.

Oculomotor Cues The oculomotor cues are created by *convergence*, the inward movement of the eyes that occurs when one looks at nearby objects, and *accommodation*, the change in the shape of the lens that occurs when one focuses on objects at various distances.

Monocular Cues Monocular cues work with only one eye. They include pictorial cues, which is depth information that can be depicted in a two-dimensional picture; and movement-based cues, which are based on depth information created by movement.

- Pictorial cues: Pictorial cues are sources of depth information that can be depicted in a picture.
- Occlusion: Occlusion occurs when one object hides or partially hides another from view.
- Relative height: Objects that are below the horizon and have their bases higher in the field of view are usually seen as being more distant.
- Relative size: When two objects are of equal size, the one that is farther away will take up less of the field of view than the one that is closer.
- Perspective convergence: When parallel lines extend out from an observer, they are perceived as converging lines, becoming closer together as distance increases.
- Familiar size: When one judges distance based on the prior knowledge of the sizes of objects.
- Atmospheric perspective: Atmospheric perspective occurs when more distant objects appear less sharp and often have a slight blue tint.

- Texture gradient: Elements that are equally spaced in a scene appear to be more closely packed as distance increases.

- Shadows: Shadows that are associated with objects can provide information regarding the locations of these objects.

- Motion parallax: Motion parallax occurs when, as one moves, nearby objects appear to glide rapidly past the observer, but more distant objects appear to move more slowly.

- Deletion and accretion: As an observer moves sideways, some things become covered, and others become uncovered.

Binocular Cues There is one other important source of depth information: the differences in the images received by the two eyes. Binocular disparity is the difference in the images in the left and right eyes.

Size Perception

The depth perception influences the perception of size. A good depth perception produces accurate judgments of size and produces bad judgments based on the size of the visual angle of the object. Examples of perception of size-dependent visual angle perception are the sun and the moon and the way one perceives objects from a plane. The principle of size constancy holds that the perception of the size of an object remains relatively constant even when viewed from different distances.

Motion Perception

Motion perception is a creation of the nervous system. People perceive motion even in the absenceof it, as when fixed lights go on and off alternately. Visual perception depends on more than one image on the retina. One observer perceives motion when follows a moving object, but the image remains in the same place in the retinas.

Movement of the observer and the movement of objects can help to more accurately perceive the shape of an object and its location in space. Perception depends on heuristics that provide estimates of what a particular stimulus. The real movement is the situation where an object moves across the visual field of the observer, is called real movement because the object moves physically. The apparent motion is the perception of movement when in fact there are two separate lights that turn on and off alternately. This apparent motion perception depends on the time between the two flashes.

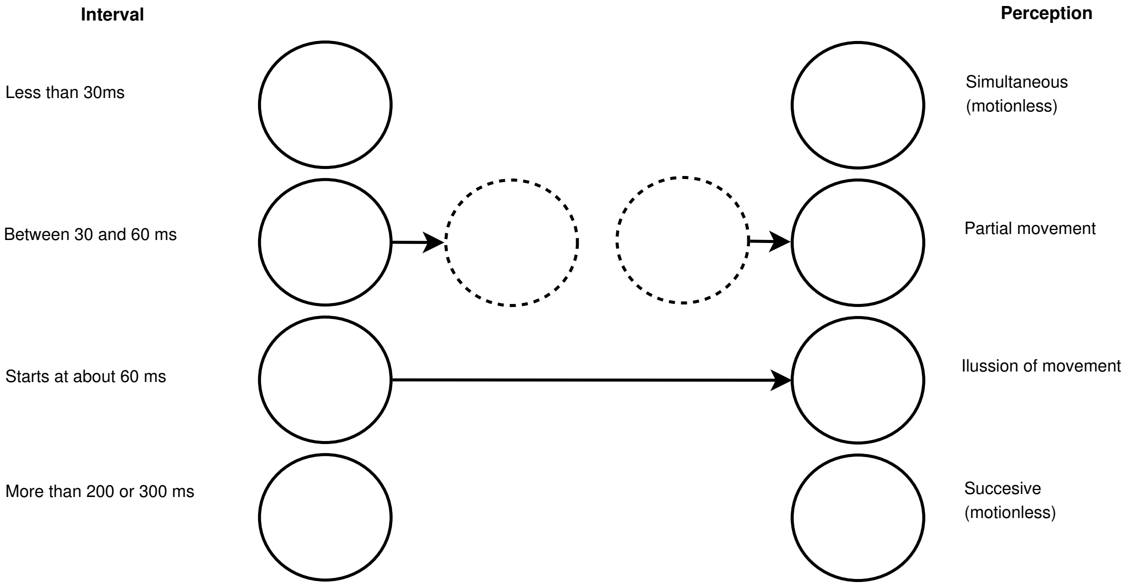


Figure 2.5 – Motion perception.

Silencing

Silencing demonstrates the close connection between the movement and the appearance of the object. Simply moving the object or the eyes can mute visual changes, making objects that had been dynamic suddenly appear static[1].

[1] http://visionlab.harvard.edu/silencing/

Perception and Action

The ecological approach to perception deals with the study of perception as it occurs in the natural environment. This approach emphasizes the connection between perception and action. The environmental information is the starting point for the analysis of this perception. The movement forms an important source of environmental information.

The optical order is the optical structure of the environment in some extent. In the static optical order, information exists, but it is possible to get more information through the movement of the observer because it generates optical flow.

The way in which visual information is used to catch a high ball probably suggest that people do not make complex calculations to determine its future course of action, but uses visual information that occurs by itself in a way that creates movements synchronized with current perceptions.

Vision is not the only sense involved in the coordination between perception and action, hearing may also be involved.

Perception Biased by Experience

Expectations, and therefore perceptions, are biased by three factors:

- The past: the experience,
- This: the current context,
- The future: the goals.

In Figure 2.6, when the sensing system is prepared to see forms of construction, the observer only sees forms of construction and the white areas between buildings are barely recorded in perception. When the perception system has been prepared to see text, the observer sees the text, and the black areas between letters barely register.

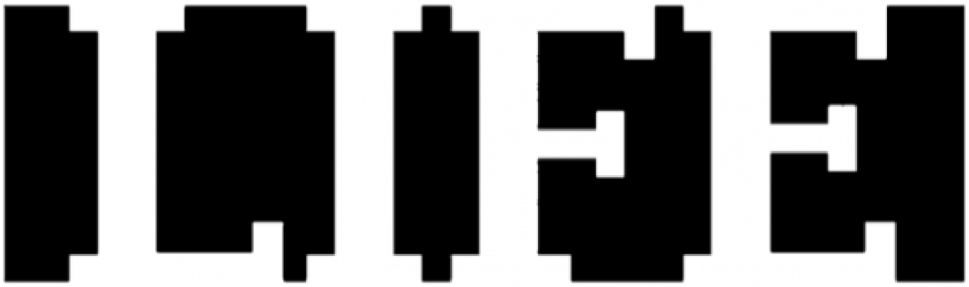


Figure 2.6 – Example of perception biased by experience: When the system was prepared to see forms of construction, one see forms of construction and the white areas are barely recorded, even when they form the word “LIFE”. (Taken from [61].)

Software users and websites often click the buttons or links without looking closely at them. The perception of the display is based more on what their experience leads them to expect that what is actually on the screen. This sometimes confuses software designers, who expect users to see the availability of the screen. But that is not how perception works. For example, if the positions of the buttons “Next” and “Return” located on the last page of a dialog box changes, many people do not immediately notice the change.

Proximity

The proximity principle has obvious relevance to the disposition of the control panels or data in software, websites and electronic applications. Designers often separate groups of controls and data display grouping them in boxes or by placing lines between groups. According to the principle of proximity, the elements on a screen can be visually grouped simply by the spacing between them, putting them closer to each other than to other controls, or group boxes without visible borders [30].

Experts recommend this approach to reduce visual clutter of a user interface. Conversely, if the controls are too far, people have trouble perceiving that are related, so the software is more difficult to learn and remember. Another factor that affects the perception of the grouping is expressed is the principle of similarity: objects that

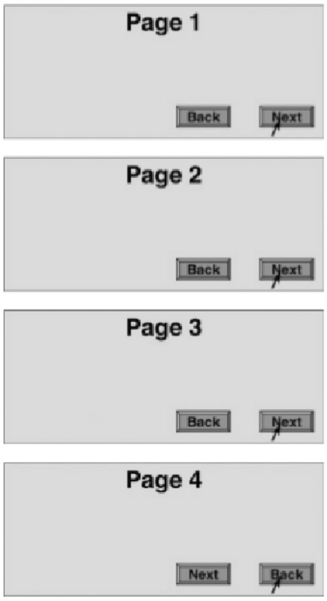
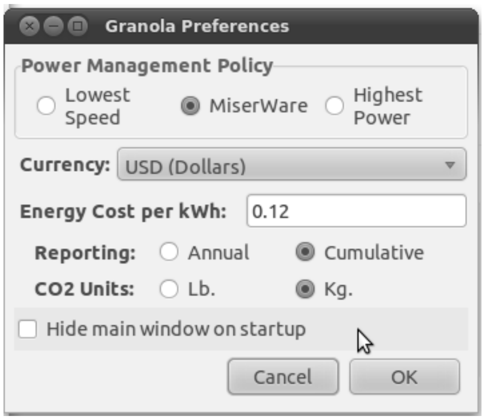


Figure 2.7 – Example of perception biased by experience: if the positions of the buttons "Next" and "Return" change, many people do not immediately notice the change. (Taken from [61].)

seem similar are grouped.



Granola Preferences

Power Management Policy

○ Lowest Speed ● MiserWare ○ Highest Power

Currency: USD (Dollars)

Energy Cost per kWh: 0.12

Reporting: ○ Annual ● Cumulative

CO2 Units: ○ Lb. ● Kg.

□ Hide main window on startup

Figure 2.8 – Example of proximity: the elements on a screen can be visually grouped using borders or putting them closer (screen capture of the Granola[2] software).

[2] http://grano.la/

Figure vs. Ground

In web design and user-interface design, the principle of figure versus ground is often used to direct primary attention to specific content. The background can convey a theme or mood to guide the interpretation of the content. Figure vs. ground is also often used to display information about the content. Content that was once the figure, temporarily becomes the background of new information, which appears briefly as the new figure.

This approach is generally best to temporarily replace the old information with new information as it provides a context that helps keep people focused in their place in the interaction.

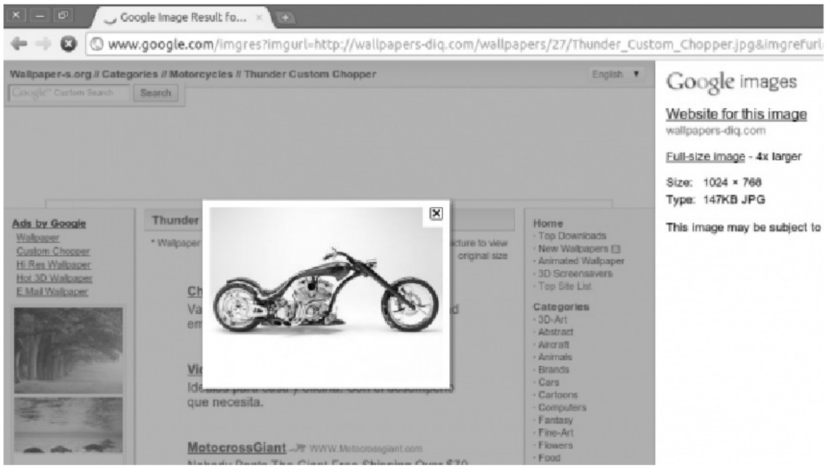
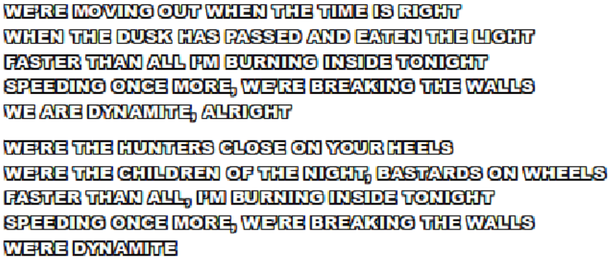


Figure 2.9 – Example of figure vs. ground (screen capture of Google Chrome).

Text

Even when the vocabulary is familiar, reading may be interrupted by writings and fonts hard to read. Context-free, automatic reading is based on recognition of letters and words by their visual characteristics. Therefore, a font with features and forms difficult to recognize it will be hard to read. Uppercase text is often hard to read because the letters seem similar. Outline fonts feature make recognition of text complicated.



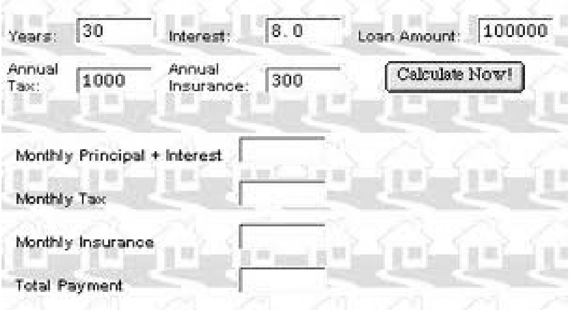
WE'RE MOVING OUT WHEN THE TIME IS RIGHT
WHEN THE DUSK HAS PASSED AND EATEN THE LIGHT
FASTER THAN ALL I'M BURNING INSIDE TONIGHT
SPEEDING ONCE MORE, WE'RE BREAKING THE WALLS
WE ARE DYNAMITE, ALRIGHT

WE'RE THE HUNTERS CLOSE ON YOUR HEELS
WE'RE THE CHILDREN OF THE NIGHT, BASTARDS ON WHEELS
FASTER THAN ALL, I'M BURNING INSIDE TONIGHT
SPEEDING ONCE MORE, WE'RE BREAKING THE WALLS
WE'RE DYNAMITE

Figure 2.10 – Uppercase text is hard to read.

Another way to make the text difficult to read in software applications, web sites, and electronic devices is the use of fonts that are too small for the readers. The visual noise on the text can interrupt recognition features, characters and words and therefore automatic reading features based on changes to a more conscious and based on the context. In software user interfaces and websites, visual noise is often a result of the designers place text on a background print or display text in colors that contrast with the background poorly.

The visual noise can also come from the text. If successive lines of text contain much repetition, readers obtain poor information about the line on which they focus, additionally it is difficult to identify the important information. Besides design errors that interrupt the reading of the user, many software interfaces simply have too much text, forcing users to read more than necessary.



Years: 30
Interest: 8.0
Loan Amount: 100000
Annual Tax: 1000
Annual Insurance: 300
Monthly Principal + Interest
Monthly Tax
Monthly Insurance
Total Payment

Figure 2.11 – Example of visual noise. (Taken from [61].)

2.2 Memory

Memory is the processes by which information is encoded, stored, and retrieved. Encoding allows information that is from the outside world to reach the senses in the forms of chemical and physical stimuli. In this first stage one must change the information so that one may put the memory into the encoding process. Storage is the second memory stage or process. This entails that one maintains information over periods of time. Finally the third process is the retrieval of information that one has stored. One must locate it and return it to the consciousness. Some retrieval attempts may be effortless due to the type of information.

Short and Long Term Memory

Recent research on memory function and brain indicate that short term memory and long term are functions of a single memory system one that is more closely linked to the perception of what is thought. The memory formation involves long-lasting changes even permanent in neurons involved in a pattern of neural activity, making it easier to reactivate the pattern in the future.

The memory activation is reactivate the same pattern of neuronal activity that occurred when the memory was formed. Somehow the brain distinguishes initial activations and reactivation of neural patterns. The more often a pattern of neural memory is reactivated, the stronger it gets; that is, it becomes easier to revive, which in turn means that the corresponding perception is easier to recognize and remember. The short-term memory, is equal to the center of the attention. The main features of the short-term memory are its low capacity and volatility. The capacity and the volatility of short-term memory has many implications for the design of interactive computer systems. The main consequence is that user interfaces should help people remember the essential information at any moment.

People do not require to remember the state of the system or what they did, because their attention is focused on the main goal and progress towards it. For example when people use a search function on a computer to find information, write the search terms, the search begins, and then review the results. The evaluation of results often requires knowing what were the search terms. If short-term memory is not limited, people always remember what they had written in search terms just a few seconds earlier. When the results appear, the attention of the individual is directed away from what he is looking towards the outcome. Not surprisingly, people who see search results often do not remember the search terms they just typed.

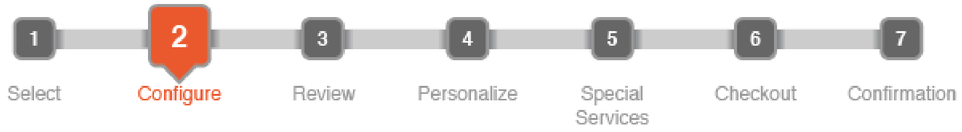


Figure 2.12 – The reservation system of an airline shows the progress of the user to know at what stage the process is[3].

It Is Easy To Recognize, It Is Hard to Remember

The relative ease with which one can recognize things rather than recall is the basis of the graphical user interface (GUI). Graphical user interface is based two rules of interface design:

- See and choose is easier to remember and type: Show users their choices and let them choose between them, rather than forcing users to remember the options and tell the system what they want. This rule is the reason why the GUI almost completely replaced by the command-line user interface in personal computers.
- Use images whenever possible to transmit function: People recognize images very quickly, and recognition of an image also stimulates recovery of associated

[3] http://www.aeromexico.com/

information. For this reason, the user interfaces are used to transmit images function as desktop icons or toolbar, error symbols, and plot options to know what stage of the process is.

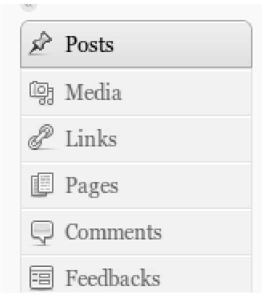


Figure 2.13 – Using icons to recognize items on a menu (screen capture of Wordpress[4]).

2.3 Learning

Learning is acquiring new, or modifying existing, knowledge, behaviors, or skills and may involve synthesizing different types of information. The ability to learn is possessed by humans, animals, and some machines. Learning is not compulsory, it is contextual. It does not happen all at once, but builds upon and is shaped by what one already knows. Learning may be viewed as a process, rather than a collection of factual and procedural knowledge.

Problem Solving and Calculation are Difficult.

People have their own objectives. They are using a computer to help them achieve a goal. They want and need to focus their attention on that goal. Interactive system designers should respect that and not distract users by imposing technical problems and objectives that users do not want. Examples of technical problems that computers and web services impose on their users include the following:

[4] http://wordpress.com/

- I want my "ID". Is that the same as my username?.
- I was charged full price! It did not gave me my discount. Now what?
- It says the software can be incompatible with a plugin already on my PC. "May be"? Is it or is not it? And if so, which plugin is guilty? What should I do?
- I want the page numbers in chapter start in 23 instead of 1, but I don't see a command to do that. I have tried page setup, document structure, and the view of header and footer, but it is not there. All that remains is to insert page numbers. But I do not want to insert page numbers: the chapter already has page numbers. I just want to change the starting number.
- This box is checked: "Align icons horizontally". If you disable it, will my icons are aligned vertically, or simply do not align?

Interactive systems must minimize the amount of attention that users must spend to operate, because it attracts cognitive resources away from the task that the user wants to do on the computer. Some design rules are:

- Indicate system status and progress of the users towards the goal.
- Guide users towards their goals.
- Instruct users exactly and explicitly what they need to know.
- Do not make users to diagnose system problems.
- Minimize the number and complexity of the configuration.
- Ask the user to use the perception more often that the calculation.
- Make the system familiar.
- Let the computer do the math.

Factors Affecting Learning

People learn faster under the following conditions: first the operation is focused on the task, simple and consistent; second the vocabulary is focused on the task-centered, familiar and consistent. The risk is low: for software design, designers must thoroughly understand user goals and tasks for which the tool is designed. Achieving this understanding requires three steps:

1. Perform a task analysis
2. Design a conceptual model focused on the task, which consists mainly of analyzing objects/actions. A conceptual model should be as simple as possible. Simpler means less concepts. The less has a user concepts to master, the better, always providing the required functionality. Less is more, with the condition that what is there fits perfectly with the goals of users and tasks.

   The consistency of an interactive system strongly affects how the user quickly progresses from a slow operation consciously monitored an automatic with faster performance. The more predictable operation of the various functions of the system is, the more consistent is the design.
3. Design a user interface based strictly on task analysis and conceptual model.

2.4 Cognitive Psychology

Cognitive psychology is the branch of psychology that studies mental processes including how people think, perceive, remember, and learn. The core focus of cognitive psychology is on how people acquire, process, and store information. Cognition involves all processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used.

Mental Models and Implementation

An implementation model (also called system model) is a representation of how a machine actually works or program. A mental model or a conceptual model is as a user imagines that the system works. For example, a person may believe that connecting an appliance to a power electric current flows through the cable as water in a hose.

People do not need to know exactly how a complex mechanism to use it, so they create cognitive representations to explain. These representations are sufficient to cover the interactions with the system, but not necessarily the functioning of the internal mechanism. In the case of software applications the differences between mental models of implementation and are very subtle, this is because the complexity makes it almost impossible for the user to see the connections between their actions and reactions of the program. Even if these connections are visible, they are inexplicable to most people.

A third model is the model represented designer or model, that is the way the designer chooses to represent the functionality of the program to the user. This representation can be or not be an accurate representation of what happens within the program. People tend to form mental models that are simpler than reality, if the designer's represented models that are simpler than the implementation model to help users better understand. User interfaces must be based on mental models rather than the implementation models. The more one looks the model represented the mental model is easier for the user to use and understand the system.

For example, the program Photoshop Express (cf. Figure 2.15) uses images to show different effects on an image, a user of this program, usually a graphic artist, is thinking about how the image will not think in abstract numbers as the brightness value or color saturation. A user's mental model need not be necessarily true or accurate, but should allow it to work effectively.

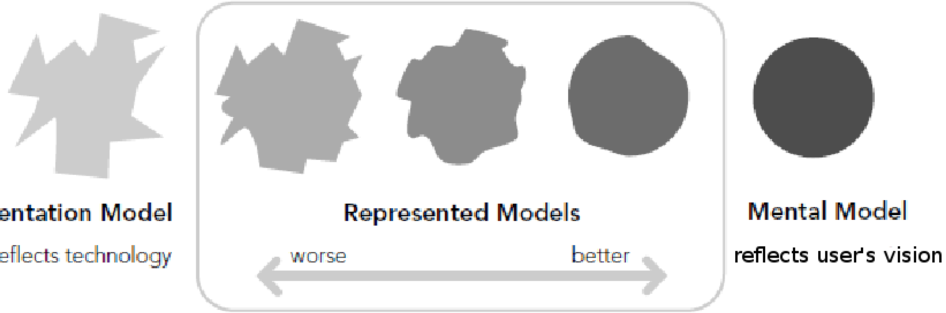


Figure 2.14 – Mental models. (Taken from [11].)

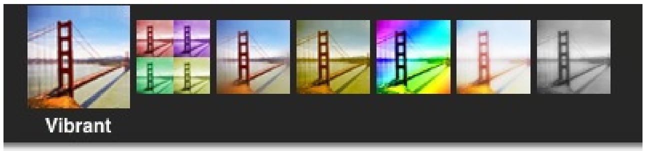


Figure 2.15 – Using images to recognize items on a menu (screen capture of Photoshop Express[5]).

Experience Levels

Most users are not beginners or experts, but intermediate. Although all users spend some time as starters, nobody stays that way for long. People do not like being incompetent, novice users become intermediates quickly or leave, no one wants to stay forever as a beginner. Most intermediate users remain in this middle state because they have more time to learn more about the product. Sometimes they use it just to complete a project, and then stop using it for months, forgetting much of what they learned. One should optimize designs for intermediate users: the goal is to turn quickly and effortlessly beginners on intermediate users, and avoid obstacles for those who want to become experts.

- Needs of beginners: A designer should consider beginners as highly intelligent and very busy, but not requiring too much instruction; the process should be

[5] `http://www.photoshop.com/tools/expresseditor`

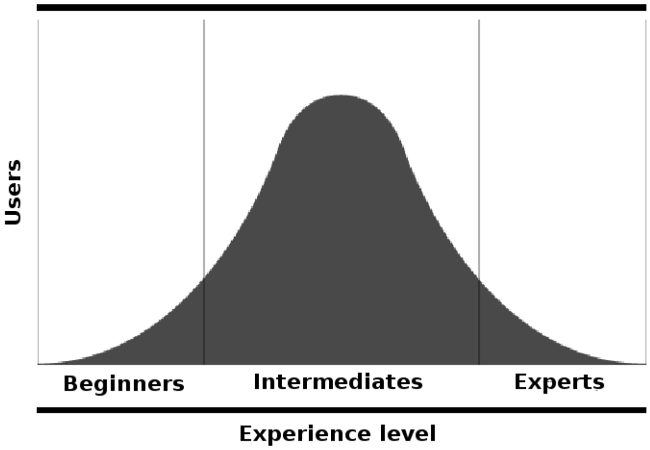


Figure 2.16 – Experience levels. (Taken from [30].)

fast and focused. People learn best when they understand the cause and effect of how things work.

- Expert needs: Users constantly looking to learn connections between their actions and the behavior of the product. Experts appreciate powerful new features. Experts call for quick access to regular working tools and want shortcuts for everything.
- Intermediate needs: Intermediate users need easy access to the tools, do not need to be explained because they already know how they work. Tooltips are perfect for intermediate user. The user will demand that work tools are located on the front and center of the interface, easy to find and remember. Intermediate users also know that there are advanced features but do not need them or not use them.

Platform and Posture

A platform is a combination of hardware and software that allows a product to work, in terms of user interaction and internal operations of the product. “Platform” is not a well-defined concept; it describes a number of important product characteristics such as physical form, size, and display resolution, input method, network connectivity, operating system, and database capabilities.

Platforms range from desktop software, websites, vehicle systems, cameras, phones, PDAs, televisions, medical equipment, scientific instruments, et cetera. To choose the right platform should be able to find a balance between the context and needs of people in addition to complying with the business restrictions, objectives and technological capabilities.

Posture is the way the product is self-presented to the users. It refers to how much attention a user requires to interact with a product and how it responds. How presented a program affects the relation between users and the product usability. If the appearance and behavior conflicts with their product seem inappropriate purposes. The appearance and behavior of the product should reflect the way is used, instead of the personal tastes of the designers, any aesthetic decision must be in harmony with the position of the product. When a product has different characteristics and different postures, the prevailing posture must be defined, but also consider the posture and context of individual characteristics.

Desktop Software

The term *desktop software* refers to all applications running on a PC. Desktop applications are divided into several positions: sovereign, transitory, and daemonic.

- Sovereign posture: The programs are monopolizing the user's attention for long periods of time. They offer a wide range of functions and features, users kept running continually and occupy the entire screen. For example: words processors, spreadsheets, e-mail applications. Sovereign application users are usually intermediate users. Applications must be optimized for use sovereign full screen. They should use conservative colors.
- Transient posture: The program comes and goes, accompanied by filing a simple function of a restricted set of controls, the application is invoked when

you need the job done quickly and then disappears by continuing the user to continue with normal activity, usually a sovereign application, for example widgets. The interface should be obvious, presenting clearly controls without confusion or mistakes. It should be simple and clear with large easy to read buttons. It must respect the sovereign application and not occupy more screen space than necessary. The program should be limited to a simple window. A transient application must remember its previous position and configuration.

- Daemonic posture: Programs run silently in the background, invisible, performing vital tasks without human intervention. For example printer drivers, networking. Occasionally demonic applications need to be adjusted, so that they become transient.

2.5 Designing Interfaces

Following user-interface design guidelines is not straightforward. Design rules often describe goals rather than actions. They are purposefully very general to make them broadly applicable, but that means that their exact meaning and their applicability to specific design situations is open to interpretation. More than one rule will often seem applicable to a given design situation. In such cases, the applicable design rules often conflict, i.e., they suggest different designs. All of the design rules are based on human psychology: how people perceive, learn, reason, remember, and convert intentions into action. Many authors of design guidelines had at least some background in psychology that they applied to computer system design [61].

Web sites

Web sites can be divided in two different categories: transactional sites and web applications.

Transactional sites include online shopping, banking, investment portals. During these activities users devote their attention to a single site, but in some cases, such as comparing products to buy, also jump between different sites, so it is important to clarify this in navigation.

Web applications include enterprise applications, publishing tools, and online documents. These applications can be presented as desktop applications that run within a browser window. These applications require the user to save each state change.

Design on Other Platforms

The platforms include: kiosks, televisions, microwave ovens, car dashboards, cell phones, et cetera. Some basic principles to consider when designing software for these platforms include the following:

- Do not think of the product as a computer.
- Integrate hardware and software design.
- Let the context guide the design.
- Use different ways to view.
- Limit the scope.
- Balance the navigation display.
- Adapt to the platform.

Flow and Transparency

Flow is the state when a person is able to focus on an activity, losing awareness of peripheral problems and distractions. To make people more productive and happy, corresponds designing interactive products to promote and improve the flow. If the application user distracts and disrupts the flow, it is difficult to maintain the productive state. If the user can achieve his or her goals without the need for the product or user interface, then he or she will. Interaction with excess software will never be a pleasant experience. No matter how great is the interface, less is always better.

To create a sense of flow, the interaction must be transparent, mechanics disappearing and leaving the person face to face with the objectives. Some rules for designing harmonious interactions:

- Follow the user's mental model.
- Less is more.
- Allow users to conduct.
- Keep tools handy.
- Provide feedback.
- Desig for the probable, provide for the possible.
- Provide comparisons.
- Provide direct manipulation.
- Reflect the status of the application and objects.
- Avoid unnecessary reporting.
- Avoid blank screens.
- Differentiate between commands and settings.
- Provide options.
- Hide the "emergency levers".
- Optimize for the answer.

Extra Load

Extra load is the work that one has to do to meet the needs as tools or external agents as while trying to reach the goal. It is difficult to distinguish because people are used to see the extra load as part of the tasks. A designer must aim to delete the extra load whenever possible. Designers often add extra load as support for first-time users or casual. These tools become burden as users become more familiar with the product. Wizards and tutorials should be able to be turned off easily.

Visual extra load causes waste of time when the user is trying to find an item on a list or determining which elements are buttons and which are decoration. Another way of extra load are interruptions, such as error messages, whenever possible, to avoid interrupting the flow of the user. Asking permission from users to make a change, or open a new window to make the change, it is also extra burden; it should be possible to make and save changes in the same place. Navigation is also an extra burden, should be avoided whenever possible. To improve navigation, the designer should:

- Reduce the number of places to go.
- Provide signs.
- Provide global views.
- Provide a suitable mapping.
- Avoid hierarchies.

Design of Good Behavior

The division of labor in the computer age is very clear: “the computer should do the job and the person should think” [61]. One should think of the computer as a co-worker with whom one has a good working relationship. Computers must be considerate, that is, worried about the needs of others. A considerate software cares about the objectives and user needs.

If an interactive product hides its processes, forces users to find the common features, and the user blame for failures, and users will have an unpleasant and unproductive experience. Users of interactive products are commonly irritated due the lack of consideration, not poor specifications. Some of the important rules for interactive product design are:

- Have an interest.
- Be respectful.
- Use common sense.
- Anticipate user needs.
- Do not load the user with personal problems.
- Keep the user informed.
- Be perceptive.
- Trust.
- Do not ask too many questions.
- Take responsibility.
- Know when to bend the rules.

INTELLIGENT PRODUCT DESIGN

Smart products remember. In order how the user perceives an interactive product as considerated and intelligent, the product must have some knowledge about the user and learn from their behavior. A product must learn important things when a user interacts with:

- Recall decisions.

- Remember patterns.

- File locations.

- “Undo” lists.

- Previous data inputs.

- Reduction of joint decisions: The product should reduce frequently used decisions to the option of do it all at once.

- Prefered thresholds: A smart product should remember thresholds used previously by the user, to avoid adjustment of preferences every time the product is used.

Metaphors

There are three paradigms on the visual design of interfaces:

- Focused on implementing: Interfaces based on understanding how things really work.

- Metaphor: Interfaces based on intuition of how things work.

- Idiomatic: Interfaces based on learning how to reach a goal.

Some designers think that filling the interface with familiar images and objects from the real-world to help users learn more easily. Top designers consider the selection of metaphor as the first and most important task. The problem of metaphors is that there are not enough, they do not scale well, the ability of users to recognize is questionable, and that there are cultural barriers. It is important for the designers never to make the interface take the form of a metaphor.

2.6 Human-Computer Interaction

Human-device interaction is designed to support explicit human-computer interaction which is expressed at a low level, e.g., to activate particular controls in this particular order. As more tasks are automated, the variety of devices increases and more devices need to interoperate to achieve tasks. The amount of explicit interaction can easily disrupt, distract, and overwhelm users. Interactive systems need to be designed to support greater degrees of human-computer interaction.

2.6.1 Vision-Based Interfaces

The use of the hand as an input device is a method that provide natural human-computer interaction (HCI). Computer-vision interaction is a natural, non-contact solution, but has some limitations. Computer vision can only provide support for a small range of hand actions under restrictive conditions. The hand gestures used in existing real-time systems are limited to a vocabulary of gestures that serve as simple commands. There have been considerable efforts to use the hand as an input device for human-computer interaction however, hand-pose estimation is still a big challenge in computer vision. There are still several open problems to be solved in order to obtain robustness, accuracy, and high processing speed. The existence of an inexpensive but high speed system is quite encouraging.

Virtual environments (VEs) should provide effective human computer interaction for applications involving complex interaction tasks. In these applications, users should be supplied with sophisticated interfaces allowing them to navigate in the virtual environment, select objects, and manipulate them. Implementing such interfaces raises challenging research issues including the issue of providing effective input/output. Computer vision has a distinctive role as a direct sensing method because of its non-intrusive, non-contact nature; it is also facing various challenges in terms of precision, robustness and processing speed requirements. Various solutions have been proposed to support simple applications based on gesture classification.

HandVu is a hand-sign vision-based recognition system that allows to interact with virtual objects. However, the used signs, although easy to understand, are not natural gestures. Finger Counter [12] is a simple human-computer interface. Using a webcam, it interprets specific hand gestures as input to a computer system in real time. The UbiHand [1, 2] is an input device that uses a miniature wrist-worn camera to track finger position, providing a natural and compact wearable input interface. A hand model is used to generate a 3D representation of the hand, and a gesture recognition system can interpret finger movements as commands. The system is a combination of a pointer position and non-chorded keystroke input device that relies on miniature wrist-worn wireless video cameras that track finger position.

An interactive screen developed by The Alternative Agency in UK is located in a department store window. The Orange screen [6] allows interaction only by moving the hands in front of the window without the need to touch it.

Sixthsense [42] is a system that converts any surface in an interactive surface. In order to interact with the system, hand-sign recognition is used. In the Sixthsense system, color markers are used in the fingers to detect the signs.

Lately it has generated great interest in the area of human-computer interaction to create more user-friendly interfaces that use natural communication. These interfaces allow the development of a large number of sophisticated applications like virtual environments or augmented reality (AR) systems. Development of these systems involves a challenge in the research of effective inout/output techniques, interaction styles, and evaluation methods [19].

Hirobe et al. [60] have created an interface for mobile devices using image tracking. The system tracks the finger image and allows to type on an in-air keyboard and draw 3D pictures. Stergiopoulou et al. [56] use self-growing and self-organized neural networks for hand-sign recognition.

[6] http://www.thealternative.co.uk/

Skin color is a common method for locating the hand because of its fast implementation. Skin color filters use the assumption that the hand is the only skin-colored object. Gesture classification is a research field involving many machine learning techniques for example: Neural Networks and Hidden Markov Model. Pose estimation involves extracting the position and orientation from the hand, fingertip locations, and finger orientation from the images.

Currently, computer vision-based interaction has some limitations in processing arbitrary hand actions. Computer vision can only provide support for a small range of hand actions under restrictive conditions. This approach has certain drawbacks in terms of natural interaction requirements. The hand gestures used in existing real-time systems are limited to a vocabulary of gestures that serve as simple commands.

Hand-pose estimation is still a big challenge in computer vision. Pose restrictions and the lack of an implementation in a real-world application indicate that there are still numerous open problems to be solved in order to obtain robustness, accuracy, and high processing speed.

2.6.2 Hand-Gesture Interaction

The use of the hand as an input device is a method that provide natural human-computer interaction (HCI). Computer-vision interaction is a natural, non-contact solution, but has some limitations. Computer vision can only provide support for a small range of hand actions under restrictive conditions. The hand gestures used in existing real-time systems are limited to a vocabulary of gestures that serve as simple commands.

There have been considerable efforts to use the hand as an input device for human-computer interaction, however hand pose estimation is still a big challenge in computer vision. There are still numerous open problems to be solved in order to obtain robustness, accuracy, and high processing speed. The inexistence of an inexpensive but high-speed system is quite encouraging.

Virtual environments should provide effective human-computer interaction for applications involving complex interaction tasks. In these applications, users should be supplied with sophisticated interfaces allowing them to navigate in the virtual environment, select objects, and manipulate them. Implementing such interfaces raises challenging research issues including providing effective input/output.

Computer vision has a distinctive role as a direct sensing method because of its non intrusive, non-contact nature; it is also facing various challenges in terms of precision, robustness and processing-speed requirements. Various solutions have been proposed to support simple applications based on gesture classification.

2.6.3 Vision-Based Pose Estimation

Lately it has generated great interest in the area of human-computer interaction to create more user-friendly interfaces that use natural communication. These interfaces allow the development of a large number of sophisticated applications like virtual environments or augmented-reality systems. Development of these systems involves a challenge in the research of effective input/output techniques, interaction styles, and evaluation methods [19].

Skin color is a common method for locating the hand because of its fast implementation. Skin-color filters use the assumption that the hand is the only skin-colored object. Pose estimation involves extracting the position and orientation from the hand, fingertip locations, and finger orientation from the images.

2.6.4 Gesture-Based Interaction Systems

Hirobe et al. [29] have created an interface for mobile devices using image tracking. The system tracks the finger image and allows to type on an in-air keyboard and draw 3D pictures (Figure 2.17).

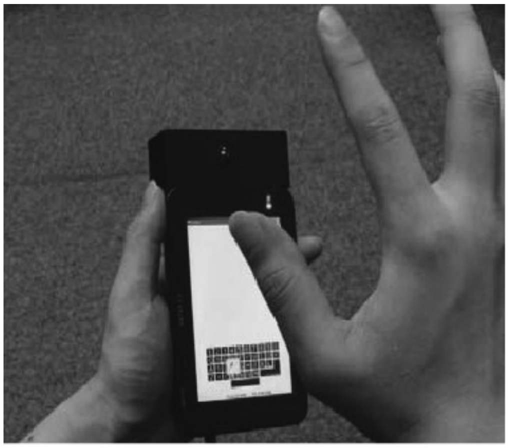


Figure 2.17 – In-air typing interface of Fastfinger [60].

Stergiopoulou et al. [56] use self-growing and self-organized neural networks for hand-sign recognition. Finger Counter [12] is a simple human-computer interface. Using a webcam, it interprets specific hand gestures as input to a computer system in real time.

The UbiHand [2] is an input device that uses a miniature wrist-worn camera to track finger position, providing a natural and compact wearable input interface.

A hand model is used to generate a 3D representation of the hand, and a gesture-recognition system can interpret finger movements as commands. The system is a combination of a pointer position and non-chorded keystroke input device that relies on miniature wrist-worn wireless video cameras (Figure 2.18) that track finger position [1].

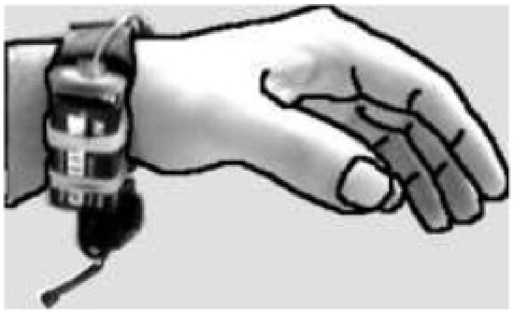


Figure 2.18 – UbiHand wrist-worn input device [2].

HandVu is a hand-sign vision-based recognition system that allows to interact with virtual objects (Figure 2.19). However the used signs, although easy to understand, are not natural gestures and have to be memorized.

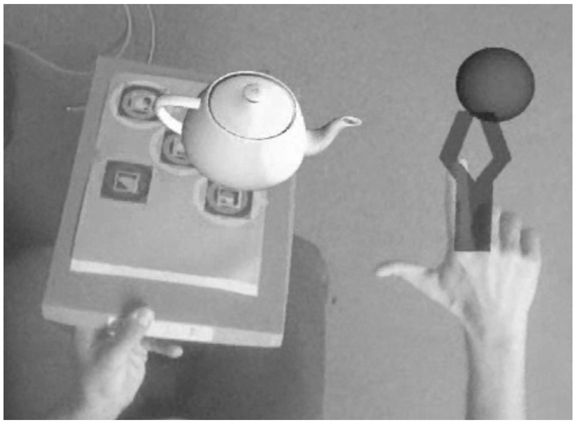


Figure 2.19 – The signs used in the Handvu system are not natural gestures[7].

An interactive screen developed by The Alternative Agency[8] in UK is located in a department store window (Figure 2.20). The Orange screen allows interaction

[7] http://www.movesinstitute.org/~kolsch/HandVu/HandVu.html

[8] http://www.thealternative.co.uk/

only by moving the hands in front of the window without the need to touch it.

Figure 2.20 – The world's first touchless interactive shop window[9].

Sixthsense [42] is a system that converts any surface in an interactive surface. In order to interact with the system, hand-sign recognition is used (Figure 2.22). In the Sixthsense system, color markers are used in the fingers to recognize the signs (Figure 2.21).

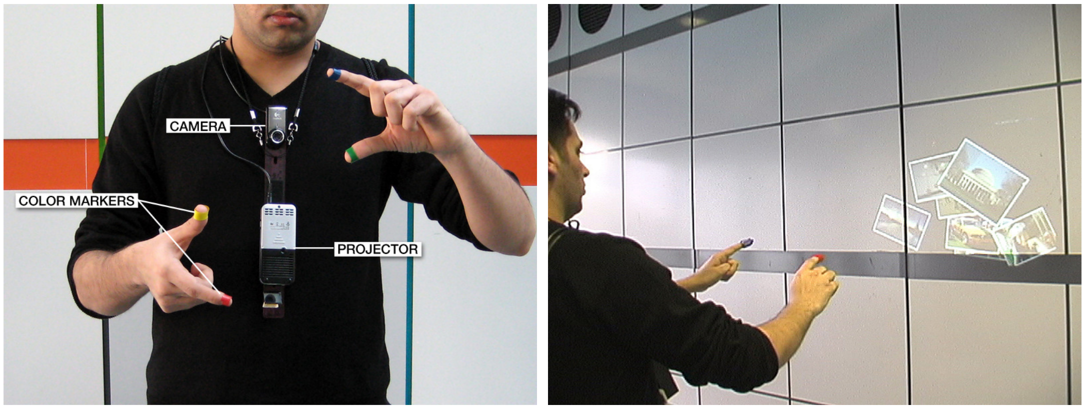


Figure 2.21 – The Sixthsense system uses a camera and a projector to convert any surface in an interactive surface [42].

Advantages and disadvantages of some related work on hand recognition are show on Table 2.1 and 2.2.

[9] http://www.thealternative.co.uk/.

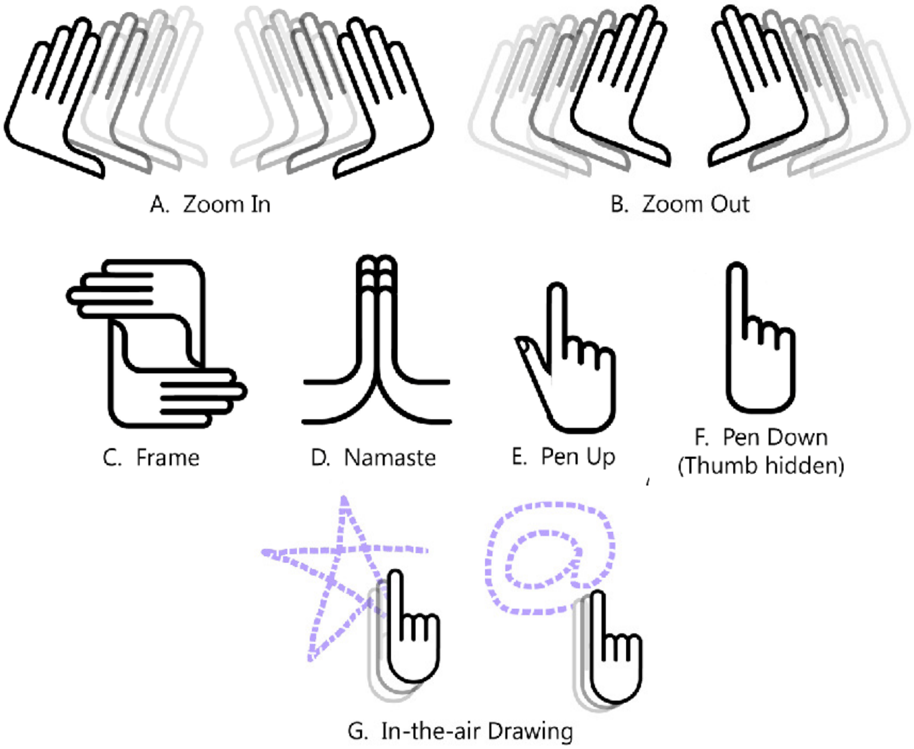


Figure 2.22 – Hand signs used in the Sixthsense system [42].

Table 2.1 – Related work on hand recognition 2001–2004.

Author	Year	Title	Application	Method	Advantages	Disadvantages
Wu [73]	2001	Capturing Natural Hand Articulation	Hand-pose recognition	Sequential Monte Carlo	Robust and accurate	Some motions not considered
Lin [38]	2002	Capturing Human Hand Motion in Image Sequences	Hand-pose estimation	Iterative Closed Point (ICP) algorithm , Monte Carlo	Accurate and robust	Image sequences
Lu [39]	2003	Using Multiple Cues for Hand Tracking and Model Refinement	Hand-pose estimation	Gradient-based optical flow constraint, forward recursive dynamic model	Difficult hand motions and conditions	Single camera sequence
Crampton [12]	2003	Counting Fingers in Real Time: A Webcam-Based Human-Computer Interface with Game Applications	Computer games	Background-differencing algorithm	Works with webcam	Few hand postures
Stenger [55]	2004	Hand-pose Estimation Using Hierarchical Detection	Hand-pose estimation	Tree-based detection	Easy to generate	Bad performance
Sudderth [59]	2004	Visual Hand Tracking Using Nonparametric Belief Propagation	Hand-pose estimation	Nonparametric belief propagation (NBP) algorithm	Effective hand tracking algorithm	Image sequences
Dewaele [16]	2004	Hand Motion from 3D Point Trajectories and a Smooth Surface Model	Hand-pose estimation	Mixed point-to-point and model-based tracking	3D models	Stereoscopic set of cameras

Table 2.2 – Related work on hand recognition 2004–2009.

Author	Year	Title	Application	Method	Advantages	Disadvantages
Bray [7]	2004	Smart Particle Filtering for 3D Hand Tracking	Hand-gesture recognition	Stochastic Meta-Descent (SMD), smart particles filter	Robustness and accuracy	Slow
Usabiaga [62]	2005	Global Hand Pose Estimation by Multiple Camera Ellipse Tracking	Hand pose estimation	Lowe's model-based pose estimation algorithm	More accurate and robust	Multiple cameras , mark
Ahmad [1]	2006	A Keystroke and Pointer Control Input Interface for Wearable Computers	Touchless input	Hidden Markov model	Mobile computers	Wrist-worn cameras
Hirobe [29]	2007	Vision-based Input Interface for Mobile Devices with High-speed Fingertip Tracking	Input for mobile devices	Lucas-Kanade	Markerless tracking	Specialized hardware
Mistry [42]	2009	A Wearable Gestural Interface	Augmented reality interaction	Simple computer-vision based techniques	Multiple hand gestures	Color marks
Stergiopoulou [56]	2009	Hand gesture recognition using a neural network shape fitting technique	Hand gesture recognition	Self-growing and self-organized neural gas	Recognition rate is very high	Slow
Terajima [60]	2009	Fast Finger Tracking System for In-air Typing Interface	Input for mobile devices	Lucas-Kanade	Markerless tracking	Specialized hardware

2.6.5 Research Challenges

Today, magnetic and electromechanical sensors (gloves) are the most effective tools for capturing hand movements [57]. These devices are expensive and have some disadvantages, hinder the natural movements of the hand and requires a complex calibration. Vision-based systems present an alternative to provide a more natural interaction. Problems with vision-based systems are the precision and processing speed. Even for a single image sequence, a real-time computer vision system needs to process a huge amount of data. On the other hand, the latency requirements in some applications are quite demanding in terms of computational power. With the current hardware technology, some existing algorithms require expensive, dedicated hardware, and possibly parallel-processing capabilities to operate in real time.

The hand has very fast motion capabilities with a speed reaching up to 5 m/s for translation and 300°/s for wrist rotation. Currently, off-the-shelf cameras can support 30–60 Hz frame rates. Besides, it is quite difficult for many algorithms to achieve even a 30 Hz tracking speed. In fact, the combination of high-speed hand motion and low sampling rates introduces extra difficulties for tracking algorithms (i.e., images at consecutive frames become more and more uncorrelated with increasing speed of hand motion) [19].

Currently, computer-vision based interaction has some limitations in processing arbitrary hand actions. Computer vision can only provide support for a small range of hand actions under restrictive conditions. This approach has certain drawbacks in terms of natural interaction requirements. The hand gestures used in existing real-time systems are limited to a vocabulary of gestures that serve as simple commands. Hand-pose estimation is still a big challenge in computer vision. Pose restrictions and the lack of an implementation in a real-world application indicate that there are still numerous open problems to be solved in order to obtain robustness, accuracy, and high processing speed (Figure 2.23).

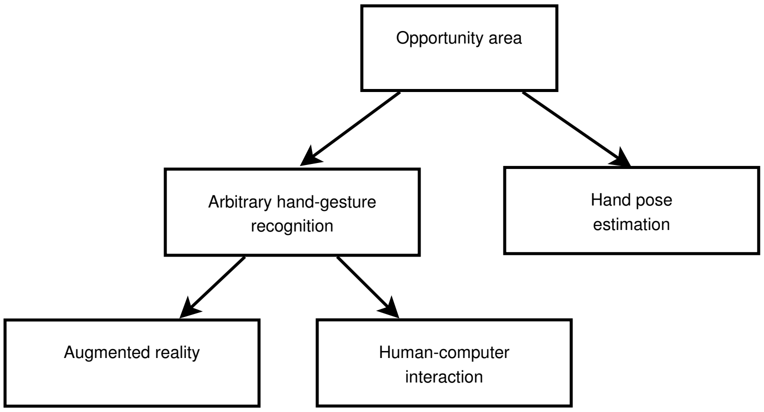

Opportunity area
Arbitrary hand-gesture recognition
Hand pose estimation
Augmented reality
Human-computer interaction

Figure 2.23 – Opportunity area.

2.7 Computer Vision

Computer vision seeks to develop algorithms that replicate one of the capabilities of the human brain: inferring properties of the external world by means of the light reflected from various objects to the eyes. A person can determine how far away these objects are, how they are oriented with respect to he or she, and in relationship to various other objects. A person can guess objects colors and textures, and can recognize them. It is also possible segment out regions of space corresponding to particular objects and track them over time.

2.7.1 Image Processing

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. The input is an image, like video frame or photograph, and the output may be also an image or characteristics associated with that image. Usually, image-processing system includes treating images as two-dimensional signals while applying signal-processing methods to them.

Image processing basically includes the following three steps.

- Import the image with optical scanner or by digital photography.
- Analyze and manipulate the image, which includes data compression, image enhancement, and spotting patterns that are not possible to detect to human eyes.
- Output is the last stage in which result can be an altered image or information that is based on image analysis.

The purposes of image processing is classified into five groups:

Visualization: Observe the objects that are not visible.

Image sharpening and restoration: Create a better image.

Image retrieval: Seek for the image of interest.

Measurement of pattern: Measures various objects in an image.

Image Recognition: Distinguish the objects in an image.

2.7.2 Video Processing

A digital video can be obtained either by sampling a raster scan, or directly using a digital video camera. Presently all digital cameras use charge-coupled devices (CCD) sensors[10]. As with analog cameras, a digital camera samples the imaged scene as discrete frames. Each frame comprises of output values from a CCD array, which is by nature discrete both horizontal and vertically. When displaying the digital video

[10] A charge-coupled device is a device for the movement of electrical charge, usually from within the device to an area where the charge can be manipulated, for example conversion into a digital value. The CCD is a major technology for digital imaging. In a CCD image sensor, pixels are represented by p-doped MOSFET capacitors. CCD image sensors are widely used in professional, medical, and scientific applications where high-quality image data is required. In applications where a lower quality can be tolerated, such as webcams, cheaper active-pixel sensors are generally used.

on a monitor, each pixel is rendered as a rectangular region with a constant color that is specified for this pixel [74].

2.7.3 Filtering

Image filtering involves the application of operations that achieve useful effects such as noise removal or image enhancement. It is used to perform various linear or non-linear filtering operations on 2D images, that is, for each pixel location in the source image its neighborhood (normally rectangular) is considered and used to compute the response. In case of a linear filter, it is a weighted sum of pixel values; in case of morphological operations it is the minimum or maximum. The computed response is stored to the destination image at the same location. It means that the output image will be of the same size as the input image. Normally, the image filters use multi-channel arrays, in which case every channel is processed independently, therefore the output image will also have the same number of channels as the input one.

Another characteristic of filters is that, unlike simple arithmetic functions, they need to extrapolate values of some non-existing pixels. For example, if someone want to smooth an image using a Gaussian filter, then during the processing of the left-most pixels in each row we need pixels to the left of them, i.e. outside of the image. One can let those pixels be the same as the left-most image pixels, or assume that all the non-existing pixels are zeros.

2.7.4 Pattern Recognition

Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest, and make reasonable decisions about the categories of the patterns.

2.8 Related Work

There are several areas where one may use the recognition of hand gestures, such as: augmented-reality systems, virtual reality, games, robot control, or sign-language interpretation. Wachs et al. [67] present some examples of applications such as medical assistance systems, crisis management, and human-robot interaction.

2.8.1 Device Interaction

On the device-interaction field, Lenman et al. [37] use gesture recognition to interact with electronic house appliances such as televisions and DVD players.

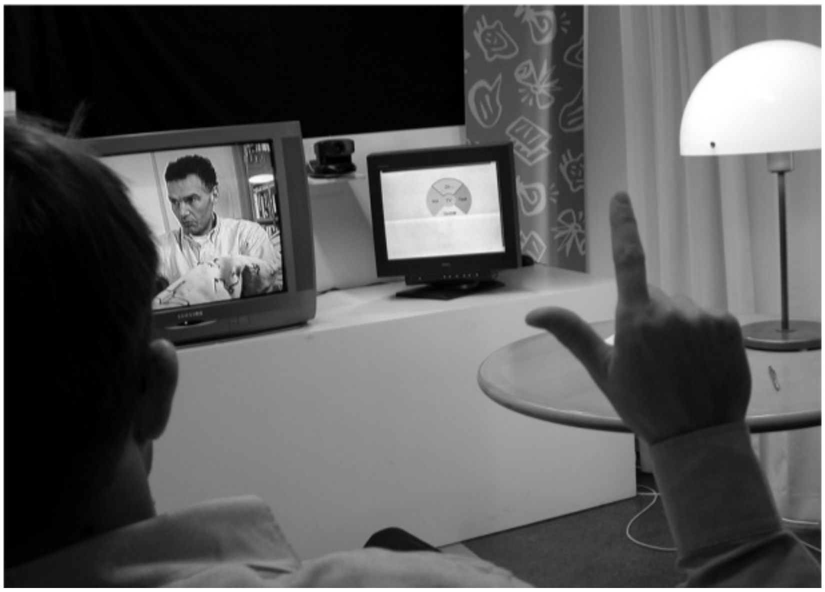


Figure 2.24 – TV gesture interaction. (Taken from [37].)

The system tracks and recognizes the hand poses based on a combination of multi-scale color feature detection, view-based hierarchical hand models and particle filtering. The hand poses, or hand states, are represented in terms of hierarchies of color image features at different scales, with qualitative inter-relations in terms of scale, position, and orientation. These hierarchical models capture the coarse shape of the hand poses.

In each image, detection of multi-scale color features is performed. The hand states are then simultaneously detected and tracked using particle filtering, with an extension of layered sampling referred to as hierarchical layered sampling. The particle filtering allows for the evaluation of multiple hypotheses about the hand position, state, orientation, and scale; a likelihood measure determines which hypothesis to chose. To improve the performance of the system, a prior on skin color is included in the particle filtering step. In order to test the system performance, Lenman et al. [37] performed only a small number of informal user trials.

MacLean et al. [40] use hand-gesture recognition for real-time teleconferencing applications. The gestures are used for controlling horizontal and vertical movement and zooming functions.

Based on the detection of frontal faces, image regions near the face are searched for the existence of skin-tone blobs[11]. Each blob is evaluated to determine if it is a hand held in a standard pose. A verification algorithm based on the responses of elongated oriented filters is used to decide whether a hand is present or not. Once a hand is detected, gestures are given by varying the number of fingers visible. The hand is segmented using an algorithm which detects connected skin-tone blobs in the region of interest, and a medial axis transform (skeletonization) is applied. Analysis of the resulting skeleton allows detection of the number of fingers visible, thus determining the gesture. To evaluate the performance of the hand-gesture processing modules MacLean et al. [40] developed a test sequence.

In order to evaluate the performance of the system ten subjects performed a sequence of gestures and showed in total 200 finger gestures. During the evaluation of the results, MacLean et al. [40] distinguished between hand gestures shown including and excluding the thumb, because the system is designed to determine if the thumb is raised or not. MacLean et al. [40] obtained an overall correct finger-counting rate of 95.4%.

[11] A blob (binary large object) is a collection of binary data stored as a single entity.

Schlomer et al. [52] use hand-gesture recognition for interaction with navigation applications such viewing photographs on a television. As input device they employ the Wii[12] controller (Wiimote) which recently gained much attention world wide. They use the Wiimote's acceleration sensor independent of the gaming console for gesture recognition. The system allows the training of arbitrary gestures by users. The developed library exploits Wii-sensor data and employs a hidden Markov model for training and recognizing user-chosen gestures.

In order to test the performance of this system, Schlömer et al. [52] create a series of tests with real users. The group of users consists of one woman and five men aged between 19 and 32 years. Each participant was asked to perform each gesture fifteen times resulting in 75 gestures per participant.

Roomi et al. [47] propose on their work a hand-gesture recognition system for interaction with slideshow presentations in PowerPoint. In this study, a Gaussian Mixture Model was used to extract the hand from a video sequence. Extreme points were extracted from the segmented hand using star skeletonization and recognition was performed by distance signature.

The dataset for the proposed study is acquired using a webcam and simulated using Matlab 7.0.[13] The open and close fists are used to represent the navigation to next slide and previous slide respectively.

Argyros and Lourakis [3] present a gesture-recognition system that allows to control remotely the computer mouse. The proposed interface permits the recognition and tracking of multiple hands that can move freely in the field of view of a potentially mobile camera system. Dependable hand tracking, combined with fingertip detection, facilitates the definition of simple and, therefore, robustly interpretable vocabularies of hand gestures that are subsequently used to enable a human operator convey control information to a computer system. As confirmed by several experiments, the proposed interface achieves accurate mouse positioning, smooth

[12] `http://www.nintendo.com/wii`

[13] `http://www.mathworks.com/products/matlab/`

cursor movement, and reliable recognition of gestures activating button events.

Crampton et al. [12] created Fingercount using a webcam, the system interprets specific hand gestures as input to a computer system in real time. Fingercount employs two computer-vision techniques: a background-differencing method adaptive to changing lighting conditions and camera movement as well a new procedure to analyze hand contours. Fingercount applications include a game designed to teach children to count with their fingers and a program that allows you to "finger paint" on a computer screen.

2.8.2 Virtual Object Interaction

The gesture recognition can also be used for interaction with virtual objects; there are several works with applications for this scenario. Wobbrock et al. [72] propose a series of gestures in order to make easier the use of interactive surfaces. They present an approach to designing tabletop gestures that relies on eliciting gestures from non-technical users by first portraying the effect of a gesture, and then asking users to perform it.

A series of experiments where performed in order to test the system. The software randomly presented 27 referents to participants. For each referent, participants performed a one-hand and a two-hand gesture while thinking aloud, and then indicated whether they preferred one or two hands. With 20 participants, 27 referents, and one and two hands, a total of $20 \times 27 \times 2 = 1{,}080$ gestures were made. Of these, six were discarded due to participant confusion.

Wachs et al. [66] use real-time hand gestures for object and window manipulation in a medical data visualization environment. Dynamic navigation gestures are translated to commands based on their relative positions on the screen. Static gesture poses are identified to execute non-directional commands. This is accomplished by using Haar-like features[14] to represent the shape of the hand.

[14] Haar-like features are digital image features used in object recognition. They are simple rectan-

2.8.3 Hand-Sign Language Recognition

Hand-sign language recognition is another common application for hand gesture recognition. Zahedi and Manashty [76] create a system for hand-sign language recognition based on computer vision. In this paper, a system for sign-language recognition using ToF (Time of Flight) depth cameras[15] is presented for converting the recorded signs to a standard and portable XML[16] sign language named SiGML for easy transferr and convert to real-time 3D virtual character animations. Feature extraction using moments and classification with nearest-neighbor classifier are applied to track hand gestures.

Zahedi and Manashty [76] create a series of test in order to evaluate the system performance. From nine sets of four different hand movements, five sets are used for training and four sets for testing. This results in 20 reference samples and 16 test samples. The permutation of five training sets that can be chosen from nine total samples is equal to 126. The training sets have been changed 126 times so that all possible combination of training and test data can be verified for consistency. In all 126 classifications of hand-gesture movements using nearest-neighbor classification, 100% classification result is achieved.

Wang and Popović [68] present on this work a gesture-recognition system that can be used on three applications: character animation, virtual object manipulation, and hand-sign language recognition. They use a single camera to track a hand wearing an ordinary cloth glove that is imprinted with a custom pattern (cf. Figure 2.25). The pattern is designed to simplify the pose-estimation problem, allowing to employ a nearest-neighbor approach to track hands at interactive rates.

gular features that can be defined as the difference of the sum of pixels of areas inside the rectangle, which can be at any position and scale within the original image.

[15] A Time of Flight Camera is a range-imaging camera system that resolves distance based on the known speed of light, measuring the time-of-flight of a light signal between the camera and the subject for each point of the image.

[16] XML stands for EXtensible Markup Language; is a markup language much like HTML; XML was designed to carry data, not to display data.

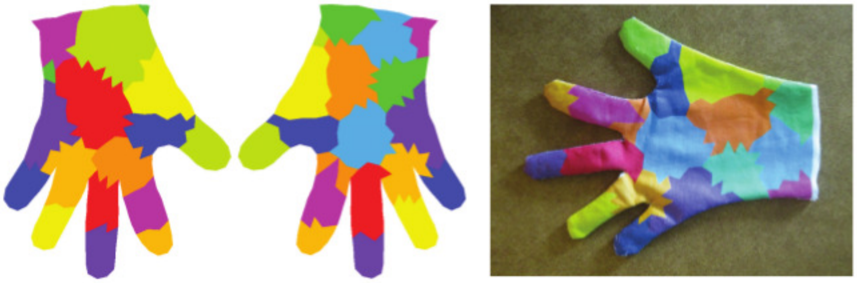


Figure 2.25 – Wang's colored glove. (Taken from [68].)

2.8.4 Robot Control

Hand-gesture recognition also can be used for robot-control applications. Çetin et al. [9] use hand-gesture recognition for remote robot control. Their approach contains steps for segmenting the hand region, locating the fingers, and finally classifying the gesture (cf. Figure 2.26). The algorithm is invariant to translation, rotation, and scale of the hand. They demonstrate the effectiveness of the technique on real imagery. Out of 105 samples taken from 21 users, they have obtained 96 correct classifications which is approximately 91% of all images used in their experiments.

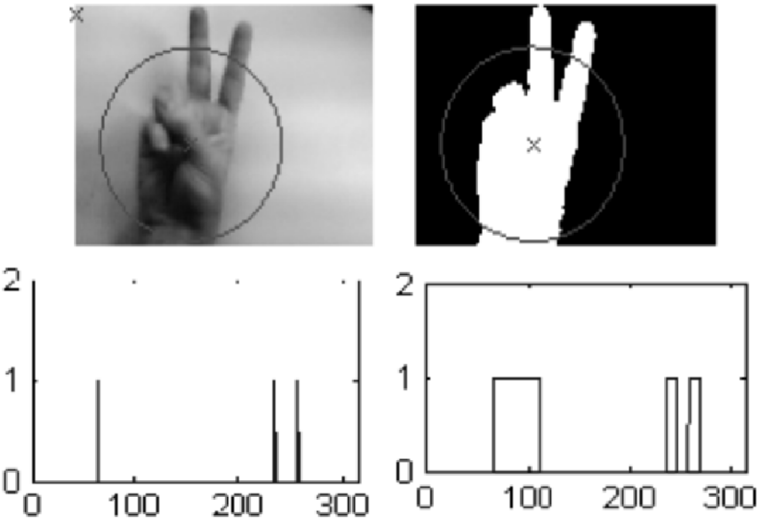


Figure 2.26 – Using zero to one transition to count fingers on a binary image [9].

Images taken under insufficient light (especially using the webcam) have led to the incorrect results. In these cases the failure mainly stems from the erroneous segmentation of some background portions as the hand region.

Chapter 3

Hand Recognition

One problem on the current augmented-reality systems is that the user needs to hold the screen in front of him while walking or driving; or in other situations where is necessary to interact with systems without touching them for example in a surgery. This can be solved combining augmented-reality systems with a natural hand-gesture interaction. In order for the users to naturally interact with the system, improvement in the hand-gesture recognition methods is necessary. An algorithm was developed to recognize hand-sign gestures based in computer-vision techniques, the system uses a webcam to recognize signs made by a user. To verify the correct operation of the algorithm, an evaluation with users was performed.

In order to recognize hand gestures we need to perform computer-vision operations (Figure 3.1) to an input image obtained from a webcam following the next procedure:

1. Having a color image input, we need to apply a skin-color filter to separate the hand from the background.

2. Using the resulting image form the skin-color filter, we need to obtain the border of the image.

3. Using the border, we calculate the convex hull, an analog descriptor of shape.

4. With the border and the convex hull, we calculate the convexity defects of the image.

5. Having the convexity defects, we can detect useful characteristics of the hand shape.

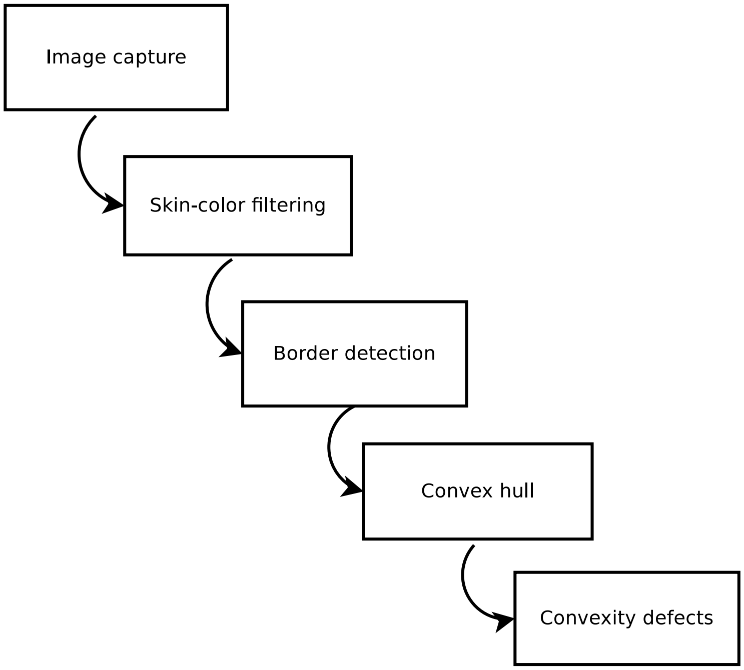


Figure 3.1 – The proposed hand-recognition procedure.

3.1 Skin-Color Filtering

Skin-color has proven to be an useful and robust cue for face detection, localization, and tracking. Image-content filtering, content-aware video compression, and image color-balancing applications can also benefit from automatic detection of skin in images. The final goal of is to build a decision rule that will discriminate between skin and non-skin pixels. This is usually accomplished by introducing a metric, which measures distance (in general sense) of the pixel color to skin tone. The type of this metric is defined by the skin-color modelling method.

Colorimetry, computer graphics, and video-signal transmission standards have given birth to many color spaces with different properties. A wide variety of them have been applied to the problem of skin-color modelling.

3.1.1 Skin-Color Filter RGB

RGB is a color space originated from CRT (or similar) display applications, when it was convenient to describe color as a combination of three colored rays (red, green, and blue). It is one of the most widely used color spaces for processing and storing digital image data.

Let I be the input image, where I_R, I_G and I_B are the image red, green, and blue channels:

$$\{I_R, I_G, I_B\} \in \mathbb{N}^{i \times j} \tag{3.1}$$

$$I_R, I_G, I_B = [i_{R_{i,j}}], \tag{3.2}$$

$$i_{R_{i,j}} \in \mathbb{N}_R \subseteq \mathbb{N}, \tag{3.3}$$

$$\mathbb{N}_R = \{0, 1, 2, ..., 255\}, \tag{3.4}$$

where i and j are the image width and height. We use a pixel-based skin detection method [33] that classify each pixel as skin or non-skin individually, independently from its neighbors. A pixel in I is classified as skin if it satisfies the following conditions:

$$I_R(x, y) > 95 \tag{3.5}$$

$$I_G(x, y) > 40 \tag{3.6}$$

$$I_B(x, y) > 20 \tag{3.7}$$

$$\max\{I_R(x, y), I_G(x, y), I_B(x, y)\} - \min\{I_R(x, y), I_G(x, y), I_B(x, y)\} > 15 \tag{3.8}$$

$$|I_R(x, y) - I_G(x, y)| > 15 \tag{3.9}$$

$$I_R(x, y) > I_G(x, y) \tag{3.10}$$

$$I_R(x, y) > I_B(x, y) \tag{3.11}$$

We create a new binary image B (Figure 3.2) where:

$$B(x, y) = \begin{cases} 1, & \text{if is skin color classified,} \\ 0, & \text{otherwise.} \end{cases} \tag{3.12}$$

3.1.2 Skin-Color Filter YCbCr

A pixel in I is classified as skin if it satisfies the following conditions:

$$I_{Yc}(x, y) > 80. \tag{3.13}$$

$$85 > I_{Cb}(x, y) < 135. \tag{3.14}$$

$$135 > I_{Cr}(x, y) < 180. \tag{3.15}$$

In contrast to RGB, the YCbCr color space is luma-independent, resulting in a better performance.

We create a new binary image B (Figure 3.2) where:

$$B(x, y) = \begin{cases} 1, & \text{if is skin color classified,} \\ 0, & \text{otherwise.} \end{cases} \tag{3.16}$$

The obvious advantage of this method is simplicity of skin-detection rules that leads to construction of a very rapid classifier [64].

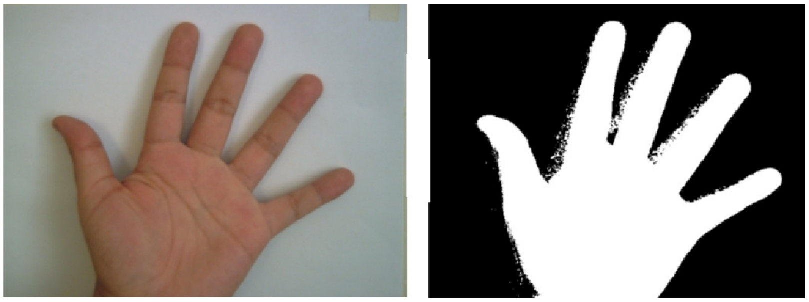


Figure 3.2 – Skin-color filter result. On the left the original image, on the right the binary image with skin-color pixels show in white

3.2 Edge Detection

Edge detection is an essential tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness has discontinuities. An edge is the boundary between an object and the background, and indicates the boundary between overlapping objects. This means that if the edges in an image can be identified accurately, all of the objects can be located and basic properties such as area, perimeter, and shape can be measured [45].

There are two main methods of edge detection: Template Matching (**TM**) and Differential Gradient (**DG**). In either case, the aim is to find where the intensity gradient magnitude g is sufficiently large to be a reliable indicator of the edge in the object. The TM and DG methods differ mainly in how they estimate g locally. Both DG and TM operators estimate local intensity gradients with the aid of suitable convolution masks (cf. Figure 3.17).

The idea behind template-based edge detection is to use a small discrete template as a model of an edge instead of using a derivative operator directly. Example masks for the Sobel 3 × 3 operator are the following:

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \; S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}.$$

One way to view these templates is an approximation to the gradient at the pixel corresponding to the center of the template. The horizontal component of the Sobel operator is S_x and the vertical component is S_y.

In the differential gradient approach, the local edge magnitude of the pixel may be computed vectorially using the non-linear transformation:

$$g = \sqrt{g_x^2 + g_y^2}. \tag{3.17}$$

For a pixel in the binary image B with coordinates (i, j), S_x and S_y can be computed by:

$$\begin{aligned} S_x &= B_{[i-1][j+1]} + 2B_{[i][j+1]} + B_{[i+1][j+1]} \\ &\quad -(B_{[i-1][j-1]} + 2B_{[i][j-1]} + B_{[i+1][j-1]}), \end{aligned} \tag{3.18}$$

$$\begin{aligned} S_y &= B_{[i+1][j+1]} + 2B_{[i+1][j]} + B_{[i+1][j-1]} \\ &\quad -(B_{[i-1][j+1]} + +2B_{[i-1][j]} + B_{[i-1][j-1]}). \end{aligned} \tag{3.19}$$

After S_x and S_y are computed for every pixel in an image, the resulting magnitudes must be thresholded. All pixels will have some response to the templates, but only the very large responses will correspond to edges. As a result we have a sequence $C \in \mathbb{R}^n$ of the contour points.

3.3 Convex Hull

The convex hull is an analog descriptor of shape, being defined (in two dimensions) as the shape unclosed by an elastic band placed around the object in question (Figure 3.5). It may be used to simplify complex shapes to provide a rapid indication of the extent of an object.

A simple means of obtaining the convex hull is to repeatedly fill in the center pixel of all neighborhoods that exhibit a concavity until no further change occurs. The algorithm is shown in the Figure 3.4.

0	1	1
1	0	0
0	0	0

Figure 3.3 – Example of a pixel neighborhood.

In the example (Figure 3.3), a corner pixel in the neighborhood is 0 and is adjacent to two 1's; it makes no difference to the 8-connectedness condition whether the corner is 0 or 1. We then get a simple rule for determining whether to fill in the center pixel. If there are four or more 1's around the boundary of the neighborhood, then there is a concavity that must be filled in.

The result is a sequence $H \in \mathbb{R}^n$ of the convex hull points.

Figure 3.4 – Convex hull algorithm [13].

```
do {
  finished = true;
    sigma = A1+A2+A3+A4+A5+A6+A7+A8
          + A1 && !A2 && A3) + (A3 && !A4 && A5)
          + A5 && !A6 && A7) + (A7 && !A8 && A1);
    if ( (A0 = 00) && (sigma > 3) ) {
      B0 = 1;
      finished = false;
    }
    else B0 = A0;
     [A0 = B0]
} until finished;
```

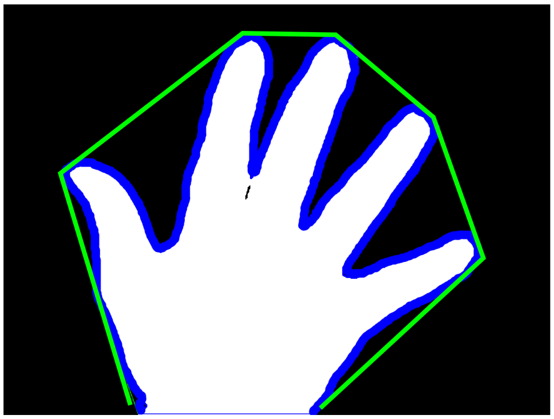


Figure 3.5 – Border (blue) and convex hull (green).

3.4 Convexity Defects

In addition, from the hand's contour and the hand's convex hull it is possible to calculate a sequence of contour points between two consecutive convex-hull vertices. This sequence forms the so-called and it is possible to compute the depth of the

ith-convexity defect, d_i (Figure 3.6). From these depths some useful characteristics for the hand shape can be derived like the depth average:

$$\bar{d} = \frac{1}{n} \sum_{i=0..n} d_i, \tag{3.20}$$

where n is the total number of convexity defects in the hand's contour.

The first step of the gesture-recognition process is to model the "start" gesture. The average of the depths of the convexity defects of an opened hand with separated fingers is larger than in an open hand with no separated fingers or in a fist.

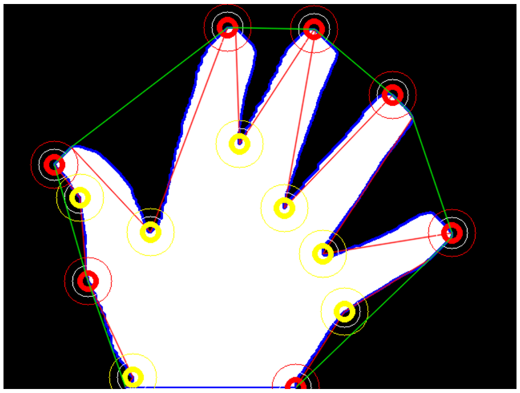


Figure 3.6 – Convexity defects (yellow), convex hull (green), and defect start-end points (red).

Chapter 4

Prototype

To test the algorithm proposed in this thesis, we created a prototype of a hand-gesture detection system, in both software and hardware. We wanted to this system to be simple, it is easy to use and to extend for use in multiple applications as we made use of open-source libraries. We wanted the system to be able to run in modest hardware, so it can be used in a mobile application.

4.1 Hardware

As the system was intended for a mobile application, we search hardware requirements (processing speed, memory, resolution) that can be easily satisfied by today mobile devices (Table 4.1). The algorithm was implemented in a computer with 1.6 GHz processor and 1 GB of RAM memory using a webcam. In our case we use a Logitech[1] QuickCam Zoom V-UW21, with 640 × 480 pixels of resolution (aproximately 0.3 MP).

Table 4.1 – Comparison of mobile devices.

Model	**CPU**	**RAM**	**CAMERA**
Samsung Galaxy S4[2]	1.9 GHz quad-core	2 GB	13 MP rear, 2 MP front
ZTE Grand S[3]	1.7 GHz quad-core	2 GB	13 MP rear, 2 MP front

[1] http://www.logitech.com

[2] http://www.samsung.com/

[3] http://wwwen.zte.com.cn/en/

Sony Xperia Z[4]	1.5 GHz quad-core	2 GB	13.1 MP rear, 2.2 MP front
BlackBerry Z10[5]	1.5 GHz dual-core	2 GB	8 MP rear, 2 MP front
Apple iPhone 5[6]	1.3 GHz dual-core	1 GB	8 MP rear, 1.2 MP front

4.2 Software

We use OpenCV[7] (Open Source Computer Vision) a library of common programming functions for real-time computer vision, and the Python[8] programing language for the implementation of the hand-recognition system.

The algorithm has a good performance and is capable of estimate in real time the number of fingers in a sign made with the hand (Figure 4.1). The procedure for the hand-recognition is as follows:

1. Get an image from the camera: The system is capable to function with a common standard webcam, in our case we use a Logitech[9] QuickCam Zoom V-UW21.

2. Resize the image: Regardless the size of the input image, we reduce this image to 160 × 120 pixels (aproximately 0.02 MP)for a faster processing. In this step we use the OpenCV function *resize()*.

3. Apply the skin-color filter: The input image is split in three different components using the OpenCV function *split()*, after that the skin-color filter rules**??** are applied in order to create a new binary image.

[4] `http://www.sonymobile.com/global-en/products/phones/xperia-z/`

[5] `http://us.blackberry.com/smartphones/blackberry-z10.html`

[6] `http://www.apple.com/iphone/`

[7] `http://opencv.willowgarage.com/`

[8] `http://www.python.org/`

[9] `http://www.logitech.com`

4. Find contours: We find the contour in the binary image using the function *FindCountours()* from OpenCV.

5. Find the convex hull: The convex hull is calculated using the *ConvexHull2()* function from OpenCV.

6. Find the convexity defects: Using the convex hull and the contour we can find the defects with the OpenCV function *ConvexityDefects()*.

7. Using the numbers of defects, estimate the number of fingers: Using the average depth of the defects, and the number of defects we can estimate the number of fingers in the image.

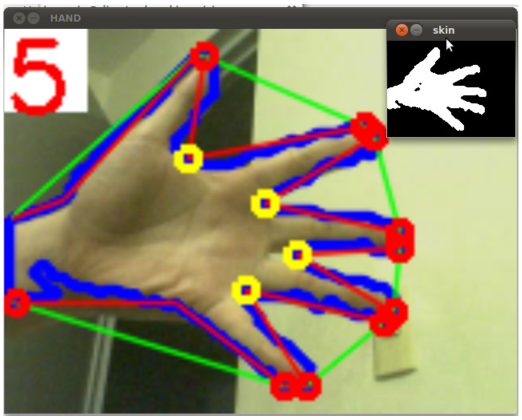


Figure 4.1 – Hand-recognition implementation. In the top right corner the result of the skin-color filter is shown; in the top left corner the recognized sign is shown; in the main image is show the input image with the convex hull and the defects.

Chapter 5

Experiments

In this chapter we present the different experiments that we use to evaluate the performance of the algorithm, user experiments and computational experiments. The user experiments were performed with real users in real time, we measure the signs detected correctly. For the computational experiment we use still frames of the signs, and we evaluate the performance when noise is introduced to the image. We also attempt to improve the algorithm using other measures as the hand-to-finger ratio.

5.1 User Experiments

The purpose of the experiments is to verify the correct operation of the first stage of the gesture-recognition algorithm. To do this verification, we performed an evaluation with users; the users perform a series of gestures that were to be correctly identified by the algorithm.

5.1.1 Setup

The users make the gestures in front of a webcam, and an observer records if the output produced by the algorithm matches with the actual gesture being made. Because variations in lighting, camera position, and background can affect the performance of the algorithm, these are controlled. Consequently, an arrangement with a fixed background, a still camera, and a source of constant illumination was created (Figure 5.1).

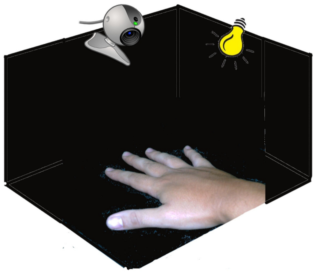


Figure 5.1 – Background, camera, and illumination arrangement.

After being instructed about the experiment, each user sits in front of the camera and place his or her right hand on the background to start making sequences of signs. Each sequence consist of a permutation of six different signs (numbers from zero to five) which was randomly generated. Figure 5.2 shows one of the sequences used.

Leaving a gap of three seconds between signs, the user performs (one sign at a time) a sequence displayed on the screen. After performing the sequence with the right hand, the user switches hands and repeats the same sequence of signs with his or her left hand now. This procedure is repeated for five different sequences.

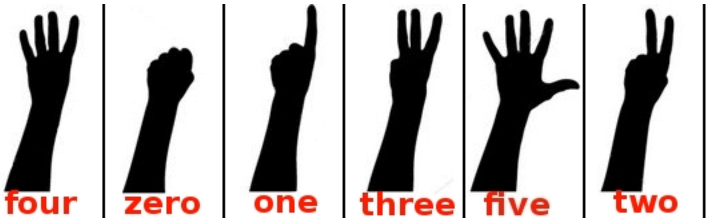
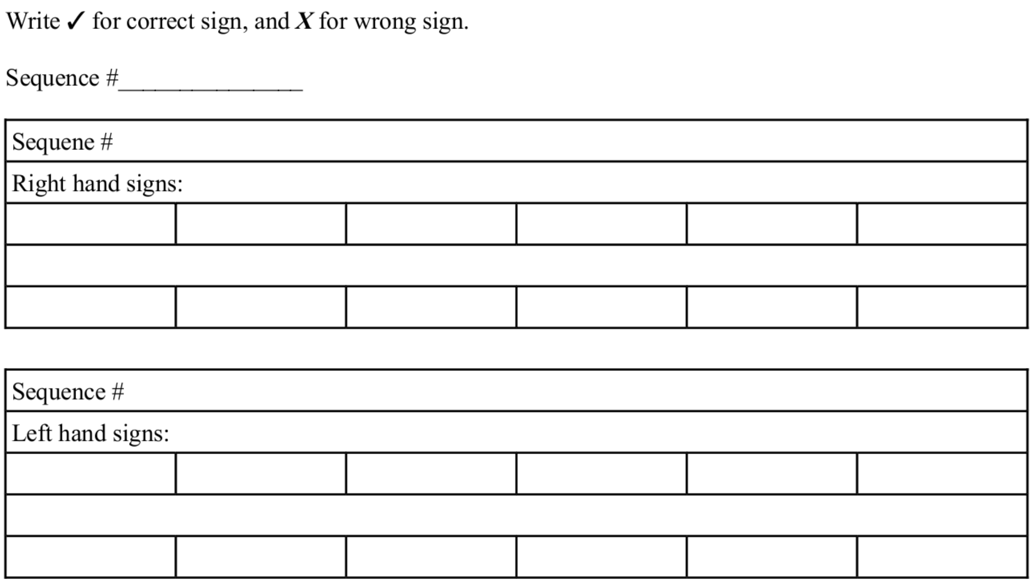


Figure 5.2 – Example of a random sign sequence.

An observer records results using a format (cf. Figure 5.3), where he marks whether the algorithm was or was not able to recognize each sign made by the user.



Write ✓ for correct sign, and *X* for wrong sign.

Sequence #_______________

Sequene #					
Right hand signs:					

Sequence #					
Left hand signs:					

Figure 5.3 – Format used by the observer (the original was in Spanish, native language of the users).

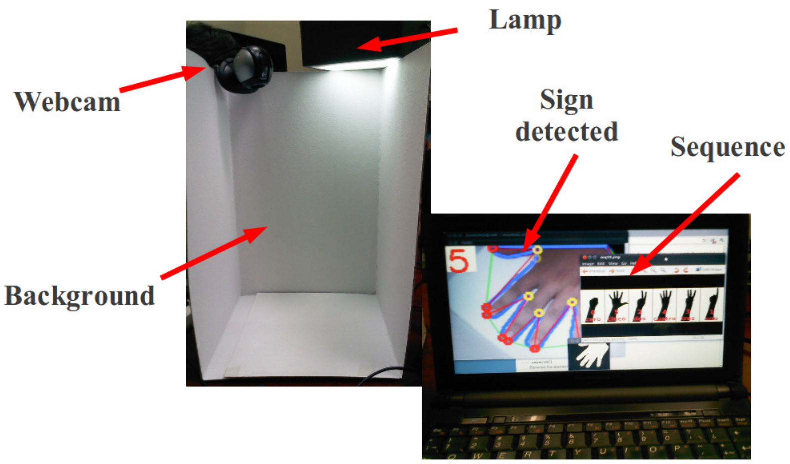


Figure 5.4 – Experimental setup.

5.1.2 First Set of Experiments

To perform the evaluation, we placed the background with the camera and the illumination next to a computer that showed the sequences and ran the sign recognition algorithm (Figure 5.4). We evaluated with seven users; each one performed five se-

Table 5.1 – First set of experimental results.

	Sign recognized						
	0	1	2	3	4	5	**Total**
Right hand	52%	56%	84%	76%	92%	92%	**75.3%**
Left hand	84%	32%	48%	88%	84%	80%	**69.3%**
Total	68%	44%	66%	82%	88%	86%	**75.3%**

quences of signs with both hands (each sequence is composed of six gestures from zero to five). Therefore, each user made 60 signs, and we have a total of 420 signs.

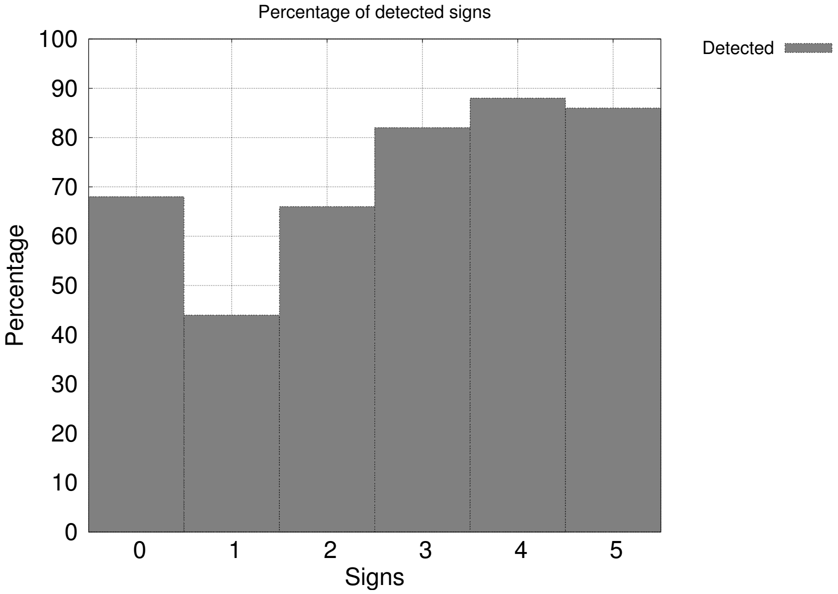


Figure 5.5 – Results for the first set of experiments.

The results of the experiment are shown in Table 5.1 and Figure 5.5. In summary, 75.3% of the signs were correctly recognized; the signs for numbers three, four, and five have the highest recognition percentage and present low variation between hands. The sign for number one, however, has the lowest recognition percentage. Also, signs for zero, one, and two show variability according to the hand used.

We conclude that the sign-recognition algorithm works correctly most of the

Table 5.2 – Percentage of correctly identified gestures.

Hand used	**Gesture recognized**						
	0	1	2	3	4	5	**Total**
Right hand	100%	72%	96%	94%	98%	100%	**93.33%**
Left hand	100%	76%	94%	96%	98%	94%	**93.00%**
Total	100%	74%	95%	95%	98%	97%	**93.17%**

time considering the conditions used in the experiments: fixed background and illumination, different users, and different hands. The primary cause for incorrect sign recognition was the particular form in which each user performs the sign; although this was partially controlled by displaying the signs to be made, these vary slightly from one user to another in a natural way (Figure 5.7). Sometimes, for example, the fingers were very close to each other, difficulting the calculation of the convex-hull defects or causing the recognition of a wrong number. In other cases, a slight twist of the wrist causes the same problems.

5.1.3 Second Set of Experiments

We evaluated the prototype with ten users; each performed five sequences of gestures with both hands (each sequence was composed of six gestures from zero to five, in random order). Therefore, each user performed 60 gestures, giving us a total of 600 gesture-recognition attempts. Table 5.2 shows the percent of gestures correctly recognized, grouped by the gesture made and the hand used.

In total, 93.1% of the gestures were correctly recognized, improving the results for a previous work [46]; the gestures for numbers three, four, and five have the highest accuracy and present low variation between hands. The gestures for number one, however, has the lowest recognition percentage. Also, gestures for zero, one, and two show variability according to the hand used. The gesture-recognition algorithm works correctly a majority of the time, under the conditions used in our

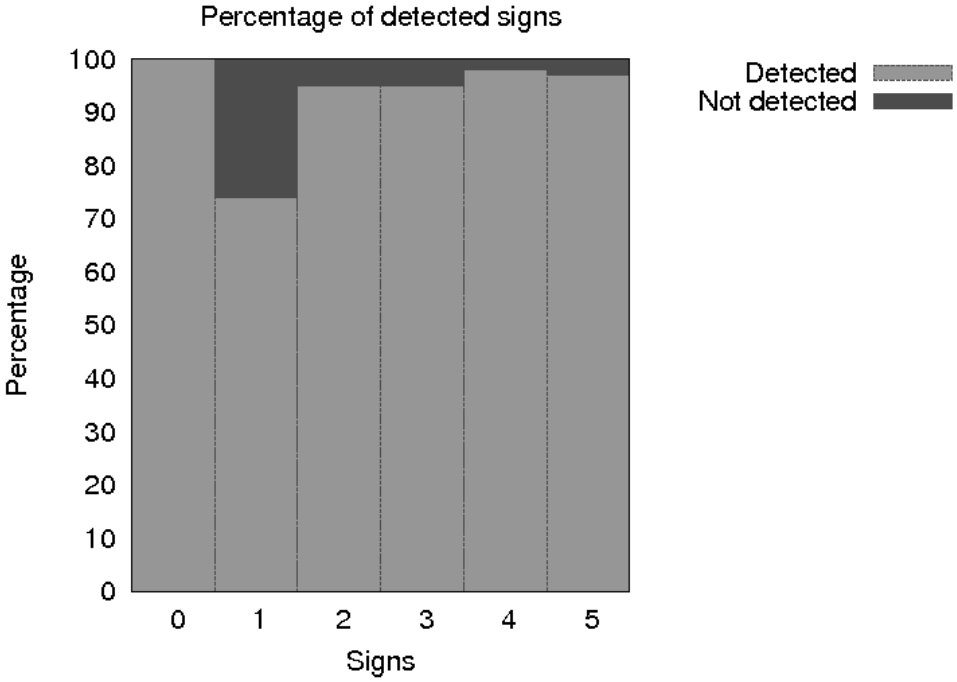
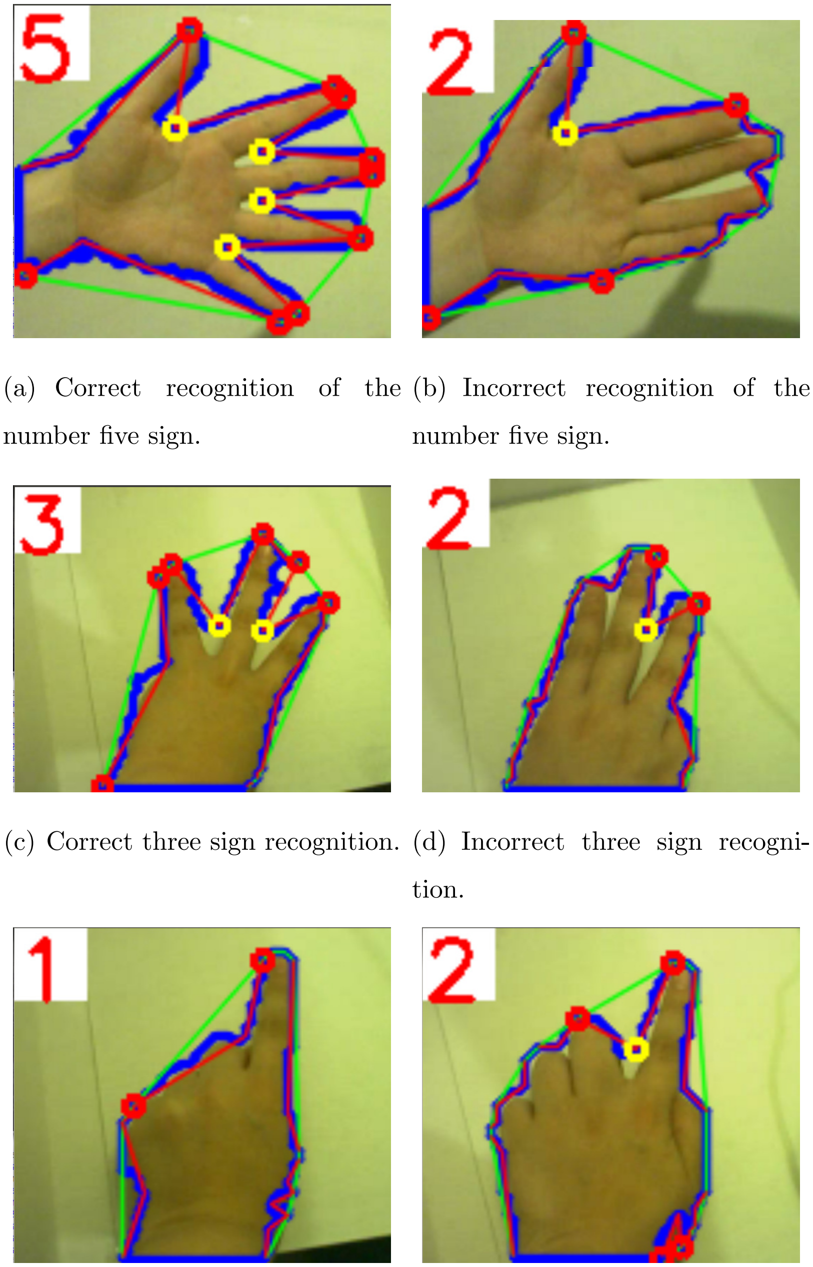


Figure 5.6 – Correctly recognized gestures.

experiments. User observation helped us notice that the primary cause for incorrect gesture recognition was the particular form in which each user performs the gesture: sometimes, for example, the fingers were very close to each other. Some examples are shown in Figure 5.7.

5.2 Computational Experiments

We use 30 different still images from each sign to perform an evaluation of the algorithm when noise is added to the image. We also seek to improve the sign detection using the area of the fingers to differentiate between signs. We test only the signs one, two, three, and four, being these the more difficult to differentiate between them. The images were taken in a light background using a standard webcam with a resolution of 1024 × 768 pixels which later was resized to 640 × 480 pixels.



(a) Correct recognition of the number five sign.

(b) Incorrect recognition of the number five sign.

(c) Correct three sign recognition.

(d) Incorrect three sign recognition.

(e) Correct one sign recognition

(f) Incorrect one sign recognition.

Figure 5.7 – Incorrect sign recognition.

5.2.1 Noise

We introduce random noise (Figure 5.8) to the original image with different levels in order to evaluate the performance of the algorithm. For generating the random noise we use the OpenCV function *RandArr* that fills an array with random numbers in our case numbers between zero and 255 for each pixel, then the generated array is added to the original image using a weighted add using values from 10% to 50% with increments of 5%. Let I be the input image and N the noise generated, the new image I' is the weighted add using the parameter $p \in \{0.1, 0.15, 0.2, 0.3, 0.35, 0.4, 0.45, 0.5\}$.

$$I' = (1 - p) \times I + p \times N. \tag{5.1}$$

In Figure 5.9 is shown that low levels of noise results in a higher number of signs detected correctly, and as the noise is increased the signs detected correctly decreases being the signs of the numbers two and three the more “noise-resistant”.

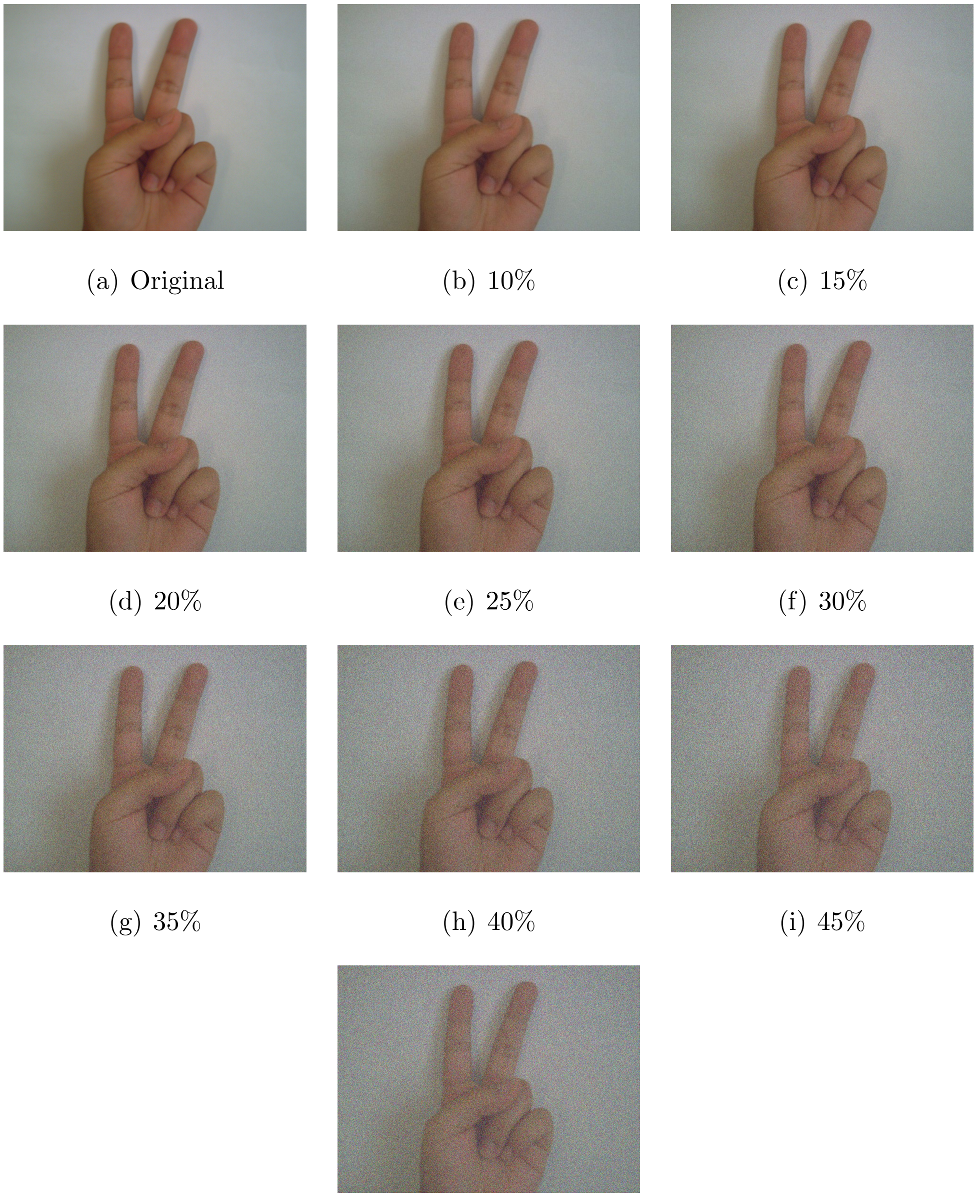
5.2.2 Area

One problem to correctly detect a sign was when the fingers were to close to each other. To deal with this problem we propose the use of the finger/hand area ratio. We calculate the ratio between the area of the fingers and the area of the hand. Thus to help differentiate the signs using the area. A number four sign would have a bigger area than a number three sign and so on. The first steps of the algorithm are the same (Figure 3.1), after the convexity defects are found the image is rotated to put the hand in a vertical position, as the middle finger length is approximately 50% of the hand length [22, 63], we cut the image by the half and calculate the area of the upper half, this being the area of the fingers.

In Figure 5.11 we see the difference between the signs, using the areas is easy to differentiate between the signs one and four, the number two and three being more difficult showing a wider range of values in the experiments.

5.2.3 Processing Time

We measure te processing time required to detect the sign, from the moment when the input image is captured to the time when the result is displayed. We obtain a



(a) Original

(b) 10%

(c) 15%

(d) 20%

(e) 25%

(f) 30%

(g) 35%

(h) 40%

(i) 45%

(j) 50%

Figure 5.8 – Random noise added to the images for testing.

mean of 270.1 milliseconds over 100 trials (Fig. 5.12). Although is a high processing time, it was proved to be adeccuate for the applications we proposed in section 6.

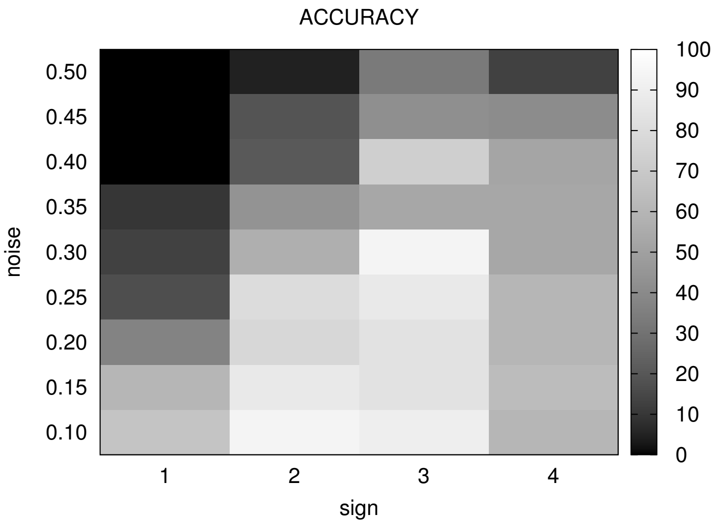


Figure 5.9 – Accuracy with different noise levels.

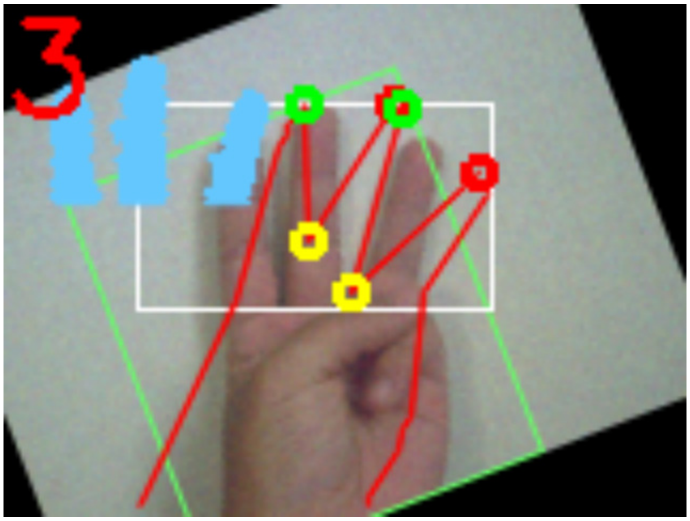


Figure 5.10 – Area used (color blue) to calculate the hand/finger area ratio. The green square is the minimum rectangle enclosing the hand, used for rotate the image. The white rectangle is the top half of the image used to find the finger area.

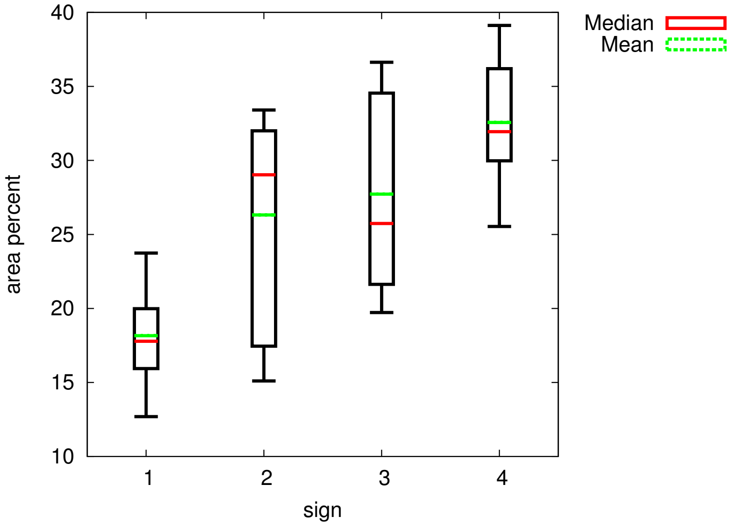


Figure 5.11 – Hand/finger area ratio.

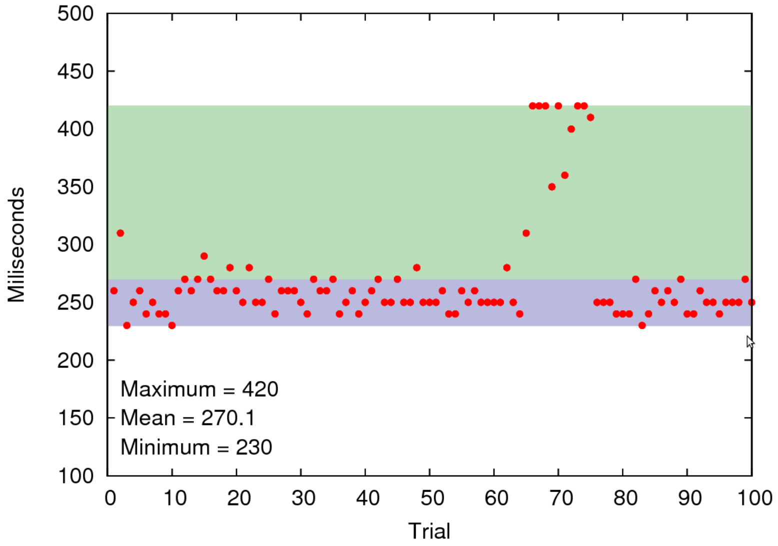


Figure 5.12 – Hand-detection processing time. The change in color indicates the mean.

Chapter 6

Proofs of Concept

Using gesture recognition, devices can be controlled remotely. Using the proposed system different prototypes were created which made use of the gesture-recognition proposed system, one for controlling a LEGO NXT robot via a Bluetooth connection, one for communication with a GPS device, and one for controlling an ARDrone.

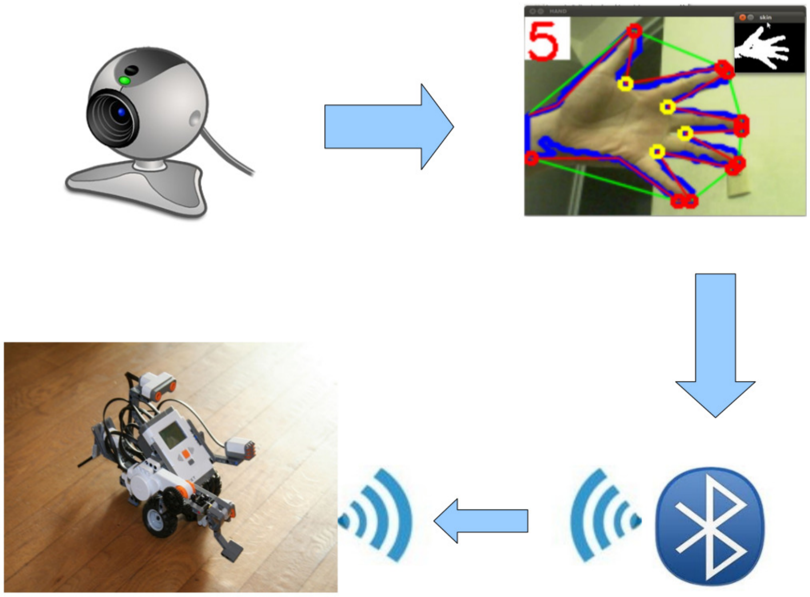


Figure 6.1 – LEGO robot prototype.

6.1 LEGO Robot

For communication with the LEGO[1] robot NXT_Python[2] libraries are used to create a connection using the Bluetooth address of the LEGO brick. If the device is found a channel of communication is created and the connection is activated. The action the robot takes is determined according to the recognized signal, andthe instructions are sent via a Bluetooth connection.

The functions of the movements are performed according to the physical configuration of the LEGO robot. In this case the robot has two wheel motors connected to ports B and C plus an additional motor port A if required by the robot configured to perform a specific action. If one wants the motor forward, both motors must be activated, if one wants the robot back off the two motors must be activated in the opposite direction. To turn left or right must be activated a motor forward and one in reverse.

6.2 GPS Device

For communication with the GPS device, we made use of a microcontroller ArduinoUNO[3], to which was added a GPS module, a digital compass, and an accelerometer (cf. Figure 6.3). Using the signal detected by the gesture-recognition system commands are sent via USB device to interact with the commands shown in Table 3. Depending on the user signal, data is obtained either from the accelerometer, compass, or GPS. When GPS data is obtained, the position is displayed in a browser window using Google Maps.

[1] `http://mindstorms.lego.com/en-us/Default.aspx`

[2] `http://home.comcast.net/~dplau/nxt_python/`

[3] `http://www.arduino.cc/en/Main/arduinoBoardUno`

Figure 6.2 – Example of turn-left function for the LEGO robot.

```
left():
  motor_left = Motor(brick, PORT_B)
  motor_left.power = 50
  motor_left..mode = MODE_MOTOR_ON
  motor_left.run._state = RUN_STATE_RUNNING
  motor_left.tacho_limit = 90
  motor_left.set_output_state()
  motor_right=Motor(brick, PORT_C)
  motor_right.power = -50
  motor_right.mode = MODE_MOTOR_ON
  motor_right.run._state = RUN_STATE_RUNNING
  motor_right.tacho_limit = 90
  motor_right.set_output_state()
```

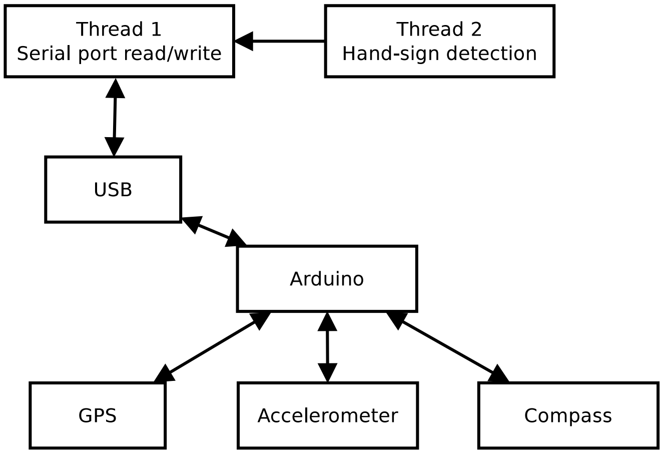


Figure 6.3 – GPS-system prototype.

6.3 AR.Drone

In the AR.Drone[4] application, the user wears an augmented-reality head set, the camera on the head set captures the hand movements; the signs are recognized by the hand-recognition system and send to the drone via wireless connection (cf. Figure 6.4).

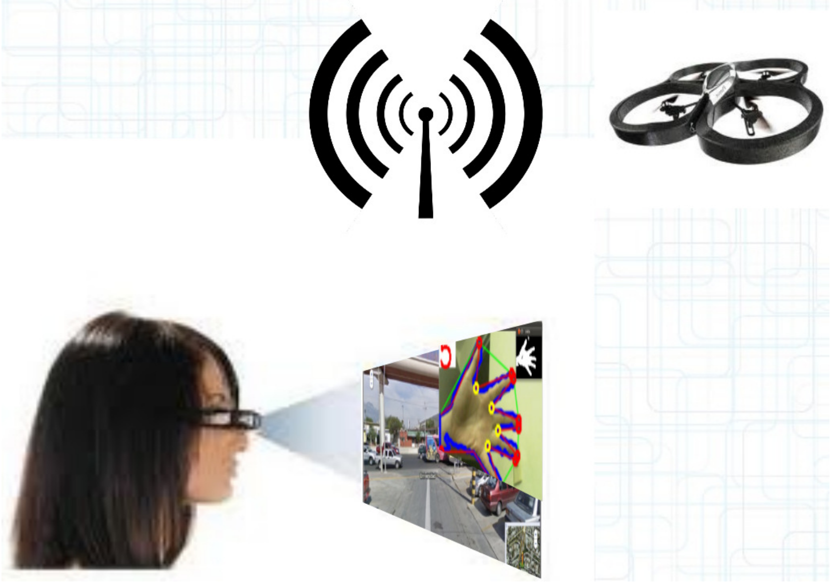


Figure 6.4 – AR.Drone-system prototype.

[4] http://ardrone.parrot.com/parrot-ar-drone/usa/

Chapter 7

Conclusions and Future Work

We presented a new method for recognizing hand gestures based on computer-vision techniques, together with an implementation that works on a ordinary webcam. The method combines skin-color filtering, border detection, convex-hull computation, and a rule-based reasoning with the depths of the convexity defects. We report users experiments on the recognition accuracy of the developed prototype, recognizing correctly three in four hand signs made on either hand, in a controlled environment. We add in the sign-recognition phase an estimate of the area of each finger. This allows us to determine whether a single finger is elevated at that position or whether multiple fingers are elevated but held together.

The finger width can be calibrated for each person by measuring the width of the hand base itself and assuming that anything that has the width between one sixth and one fourth of the base width is a single finger. The number of fingers in a wider block can be estimated as the width of the block (computable from the points used for finger counting at present) divided by one fifth of the base width, rounded down to the preceding integer value.

Another aspect that needs to be addressed in future work is the sensibility of the system to lighting conditions, as this affects the skin-color filtering, particularly with reflections and shadows. We expect these additions to improve the accuracy of the recognition system, as well as ease the cognitive burden of the end user as it will no longer be necessary to keep the fingers separate, something that one easily forgets.

Part of this thesis work was presented with the title "A Tool for Hand-Sign Recognition" [46] on the Mexican Congress on Pattern Recognition (MCPR 2012) held in Huatulco, Mexico. Proceedings of the conference was published in the Lecture Notes in Computer Science series by Springer.

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Ficha autobiográfica

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