Fusion of Artificial Vision and GPS to Improve Blind Pedestrian Positioning

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***Abstract*— Orientation and mobility are tremendous problems for Blind people. Assistive technologies based on Global Positioning System (GPS) could provide them with a remarkable autonomy. Unfortunately, GPS accuracy, Geographical Information System (GIS) data and map-matching techniques are adapted to vehicle navigation only, and fail in assisting pedestrian navigation, especially for the Blind. In this paper, we designed an assistive device for the Blind based on adapted GIS, and fusion of GPS and vision based positioning. The proposed assistive device may improve user positioning, even in urban environment where GPS signals are degraded. The estimated position would then be compatible with assisted navigation for the Blind. Interestingly the vision module may also answer Blind needs by providing them with situational awareness (localizing objects of interest) along the path. Note that the solution proposed for positioning could also enhance autonomous robots or vehicles localization.**

***Index Terms*— Computer vision, Global Positioning System, Geographic Information Systems, Sensor fusion, Blind, Assistive technology, Navigation.**

I. INTRODUCTION

As shown in numerous studies, mobility appears to be the most problematic issue in the visually impaired (VI) population. In the largest survey made in France by Ministry of Health, 58% report troubles in outdoor [1], and almost one third of the whole VI population confess not being able to move by themselves. If we only consider subjects with severe impairment or total blindness, these proportions dramatically increase, with about nine persons out of ten having strong difficulties.

Navigation in the Blind population raise problems related to Orientation (knowing where one is, and being able to go the desired destination) and Mobility (e.g. obstacle avoidance, maintaining consistent headings, estimating distances and angles). Several approaches have been conducted over the last 40 years to address the key issues relevant to Blind mobility and orientation (see [2] for a large survey). They can be classified into two main categories: Electronic Travel Aids (ETAs) and Electronic Orientation Aids (EOAs). ETAs are designed to improve mobility by detecting obstacles in the surrounding. They are usually based on ultrasonic or laser telemeters that measure the distance to features, and restitute distance information by tactile vibrations on the fingers or sound generation [3]. In order to improve autonomy, EOAs provide the Blind with some degree of situational awareness and guidance in unknown environments. Up to now EOAs are mainly based on GPS and Location Based Services. Some commercial devices are available (see e.g. Trekker, BrailleNoteGPS [4], or Kapten [5]), but in most cases, their use has been limited by relatively high price (approximately $2000) and limited precision (approx. 10m), especially in urban areas. In this paper, we focus on the issue of positioning that is the most problematic limitation in EOA for the Blind.

II. PROBLEM STATEMENT

An Electronic Orientation Aid for the Blind is usually made of 3 important components: 1/ A positioning module based on GNSS; 2/ a Geographical Information System (GIS) with a spatial database and analytical tools like route selection or user-tracking; and 3/ a User Interface (UI) that relies on non-visual (e.g. speech or tactile) interaction. However, positioning precision is rarely better than 10 to 20 meters, in many environments such as areas with high buildings, or trees, and under certain climatic conditions these performances can even drop to 30 to 50 meters error. As a result, those devices are not accurate enough to guide visually impaired users, and most EOAs based on regular GPS have shown to be unusable in real life conditions.

To overcome these limitations, different research projects suggested using Differential GPS (DGPS) that reduces the nominal error range from 10-20 meters to less than 1 meter in ideal conditions [6-8]. This technology requires an expensive network of fixed, ground-based reference stations that are not available everywhere. For the user, additional drawbacks come from the price of the commercial service added to the equipment cost, as well as the weight and the size of the receiver (at least 0.5 kg), that are not suited to pedestrian mobility.

Other systems combine GPS signals with inertial sensors to provide an estimate of the user motion after satellite loss through dead-reckoning algorithms [9], [10]. Of course the reliability of the dead reckoning methods decreases with the duration of signal loss, as it integrates the changes in position since the last fix, cumulating the drift over time. This solution is then appropriate for brief GNSS signal loss but not for long and frequent degraded GPS signals as it happens in urban areas. Hence, though this technique is useful in several situations, it must be completed by other strategies.

In this paper, we present a new class of assistive device, as part of the NAVIG project [11], based on artificial vision and geolocated visual landmarks that will allow the refinement of positions estimated by a GPS receiver. This precise localization method combined with a GIS adapted to Blind needs opens new perspectives for the visually impaired population in terms of mobility and space representation.

III. EMBEDDED VISION FOR USER POSITIONING

Our vision module features two distinct and fundamentally different functions that we named "object-localization" vs. "user-positioning". The "object-localization" function is used for locating an object requested by the visually impaired user (e.g. a mailbox). It then renders the object position in a head-related reference frame through virtual 3D sounds. This function is very important as it restores a functional visuomotor loop allowing the blind user to move the body or the hand to targets of interest. It will not be further described here as it concerns the assistive aspect of the device rather than the positioning (see [11], [12] for details).

In the second - "user-positioning" - function, the system is used to detect visual targets that are not displayed to the user, but used as anchors to refine the current GPS position. Note that it is not the user who needs to determine the particular set of visual targets to be loaded. Instead, the system automatically loads the models corresponding to the rough location of the user given by the GPS. This selection of potential targets is crucial as the total number of models within the city would be too high to be tested in real-time conditions. As all of these visual targets are geolocated and tagged in the geographical information system presented in section IV, the vision algorithm only needs to look for models in the neighborhood of the user.

A. *SpikNet recognition algorithm*

For both functions (object-localization and user-positioning), we needed an algorithm fast enough for real-time target detection and localization (i.e. compatible with pedestrian mobility). Most of the fastest pattern matching algorithms rely on an initial learning stage that extracts characteristic features from the pattern to recognize. The precision and processing speed of these methods depend on the number and the quality of the extracted features. Many of them can achieve rapid matching but are not rotation and/or scale invariant. Other methods, e.g. SURF [13] and SIFT [14], are robust to changes in scale and position but are slower, and may be restraining in real-time applications. For our system, we chose the SpikeNet library, which provides fast processing algorithms – based on human visual research [15], [16] – and good invariance properties to noise, illumination, scale or rotation.

The SpikeNet recognition engine [17], a biologically inspired image processing library developed in CerCo, uses a model for each visual pattern that needs to be recognized. The model structure consists in 30x30 patches, and thus requires relatively little memory – just a few kilobytes. As a consequence, millions of models can easily be stored in our wearable device and loaded when needed depending on the task requirements.

Of course, the critical question concerns the speed at which the recognition engine can locate visual features within an image. Speed depends very strongly on the size of the input image and the size of the targets, which explains our choice of 320 by 240 pixels images. This low resolution view is suitable for localizing objects down to about 6° of visual angle (corresponding to a 30 by 30 pixels patch in the low resolution

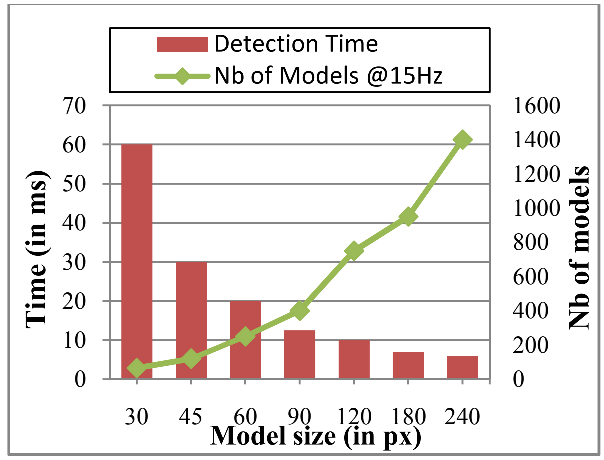

Fig. 1. Processing time for 40 models in a 320 by 240 pixels image as a function of model size. The green curve shows the maximum number of models detected with a 15Hz frame-rate.

image). For relatively large targets, the performance of SpikeNet can be very impressive. For example, on our experimental setup (Intel i7 notebook) it was possible to maintain recognition at around 15Hz using 320 x 240 pixel images and loading about 1000 different models that are 180 pixels across, as shown in Fig. 1.

B. *Prototype and concept*

In our first prototype, illustrated in Fig. 2, the user wears a head-mounted device equipped with 2 cameras that send visual information to a portable computer used for video-processing and other algorithms required by our device. The head tracking system was an Xsens Mti composed of 3-axis accelerometers, a magnetic compass and gyroscopes. For video input we have used a Bumblebee stereo-camera, commercialized by Point Grey Research, which provides a roughly 100° field of view with a resolution up to 640 by 480 pixels. The image captured by the cameras was processed by SpikeNet.

When walking along a street, SpikeNet is used to locate easily recognizable targets corresponding, for example, to visually distinct features such as shops front, buildings front or

Fig. 2. NAVIG prototype including a GPS receiver, a stereoscopic camera and a head motion tracking device mounted on a helmet. Microphone and headphones were added for speech and audio

Fig. 3. Examples of visually tracked landmarks (a bike station, road sign, public bench and shop sign)

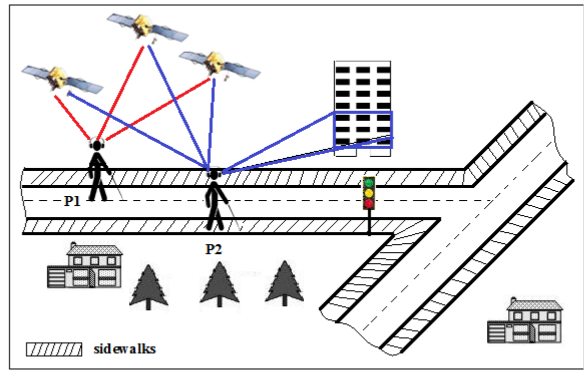

Fig. 4. User positioning P1 is the result of map matching GPS signal with current commercial GIS. Using a GIS adapted to Blind navigation (including pedestrian areas and visual geolocated targets), the user position P2 is estimated with a better precision, which is compatible with Blind navigation.

guide sign (see Fig. 3). The algorithm returns the coordinates of these targets as the centroid of the object in the image reference frame. Instead of running a parallel detection on both cameras, we found it more efficient to apply the algorithm on only one camera. It decreases computational cost and, as a result, increases the system frequency. In addition, preliminary experiments showed that it was more accurate to use the matching method from Point Grey SDK – which consists in a Laplacian of Gaussian filtering and a pixel correlation using Sum of Absolute Differences criteria – to determine the coordinates of the object in the second image rather than running another detection which could lead to imprecision, even when using epipolar constraints. Finally, the 3D position of the target in the head centered reference frame is computed from these two coordinates using the stereoscopic disparity and the calibration matrices of the lenses.

IV. Adapted Geographical Information System

Current EOAs for the Blind (Trekker, BrailleNoteGPS [4], or Kapten [5]) use standard commercial GIS generally provided by TeleAtlas or NavTeq. These GIS are mainly based on road networks and are designed for vehicle navigation only. It is obvious that they are not adapted to pedestrian navigation due to the lack of primary information corresponding to pedestrian mobility (e.g. absence of sidewalks or pedestrian crossing). Indeed, when based on these inadequate commercial GIS, map matching methods – which align a sequence of observed positions with the road network on the digital map (see e.g. [18], [19]) – result in user positioning on the center of streets (see P1 in Fig. 4). This approximation is not compatible with Blind mobility. Brainstorming sessions with blind users and Orientation and Mobility (O&M) instructor [20] showed that Blind guidance requires accurate positioning and precise instructions. An EOA must estimate in real time (compatible with walking) and with good accuracy (less than one meter) with good accuracy (less than one meter) if the user walks on the right or the left sidewalk, if he is standing in front of the pedestrian crossing, or if he has already started to cross the street, etc.

To overcome this problem, it is important to clearly identify Blind needs and then propose a novel annotation of geographical targets that have to be inserted in the GIS database. An interesting classification has been proposed by [21]. They suggest dividing pedestrian features into four general classes: (1) transportation (e.g. roads, bike paths, walkways, car parking areas, bike parking), (2) buildings (e.g. permanent and temporary), (3) land use (e.g. open space, recreation, vegetation), and (4) other objects (e.g. light poles, telephones, and stairs). Such classification can be used to group different features in categories which can help to prepare itinerary, to create a mental image of the environment, and allows a better pedestrian localization. In a previous paper related to route selection for blind pedestrian [22], we extended the work of [8], and we proposed a classification of geographical data suited for a GPS and vision-based EOA. The proposed annotation took into account two main types of data:

1/ Data used for more accurate navigation and space perception; respectively walking areas [23] (e.g. sidewalks, and pedestrian crossings) and points of interest (public buildings, shops, etc.). This data is arranged on a graph composed of nodes and edges representing all the walking areas, in addition to vehicles pathway. An adapted route selection algorithm applied on that graph selects the optimal route according to Blind needs (e.g. avoiding a complex crossing), and allows to inform the user about his surrounding during the travel (e.g. presence of a bus station).

2/ Data used for user positioning. In a vision-based EOA, it consists in geolocated and easy to detect visual points.

In the next section we show that when relying on such an adapted GIS, and on the fusion of GPS and vision signals, the system can provide a better estimate of user positioning, which is compatible with Blind mobility (See P2 in Fig. 4).

V. Data fusion for accurate user positioning

Improvements in computer hardware, cheap cost of cameras and increasingly sophisticated computer vision algorithms have contributed to develop systems where the recognition and localization of visual features help navigation, from autonomous robotics to assistive technology.

The main stream approach is to track a set of arbitrary visual features (which are both perceptually salient and visually distinctive to be detected robustly, see [24], [25]) to estimate the robot egomotion and to build a local map of the environment. This technique, named SLAM (Simultaneous localization and mapping [26]), usually requires an independent set of sensors to compute the robot motion over time. If inertial odometry is quite accurate for wheeled robot and vehicles where angle of steering and wheel encoders can provide a reliable estimate of the motion from a starting location, it is much more complex in the case of pedestrian. Indeed, the motion of a walking person exhibits high variation in velocity and trajectory, and the estimate of the number of steps, step length and heading from pedometers and accelerometers is usually not accurate enough. Moreover visual odometry as well as inertial odometry inevitably accumulate error if they are not corrected with an absolute reference, which results in an increasing drift with time. For these reasons we proposed the use of visual landmarks with known geographic position (given by the GIS database presented previously) to refines the pedestrian position estimated by a GPS. To our knowledge very few authors proposed such architecture [27].

In our system, the first estimate of user position was provided by a GPS receiver combined with a wearable inertial navigation system. This set of sensors (accelerometers, electronic compass and pedometer) allowed to compute the user position, speed and orientation by fusion of GPS positions and dead-reckoning navigation, using an Extended Kalman Filter as proposed in [28], [29]. This position was then refined by the “user-positioning” function of the embedded artificial vision and a map matching method [18].

As shown in section III, the vision module returned positions of visual landmarks detected along the path of the user. Once a model was recognized, the vision agent sent the ID of the target as well as its 3D coordinates in the head referential. The inertial sensors and magnetometer placed on the helmet provided the user's head orientation (yaw, pitch and roll angles). As shown in equation (1), the rotation matrix of each Euler angle was multiplied with the target coordinates in the head reference frame (x,y,z) in order to obtain the target coordinates in the map referential (x',y',z'). The altitude (z') was not used later on as we assumed the pedestrian was on the ground.

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} . \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(yaw) & \sin(yaw) \\ 0 & \sin(yaw) & \cos(yaw) \end{bmatrix} . \begin{bmatrix} \cos(pitch) & 0 & -\sin(pitch) \\ 0 & 1 & 0 \\ \sin(pitch) & 0 & \cos(pitch) \end{bmatrix} . \begin{bmatrix} \cos(roll) & \sin(roll) & 0 \\ \sin(roll) & \cos(roll) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

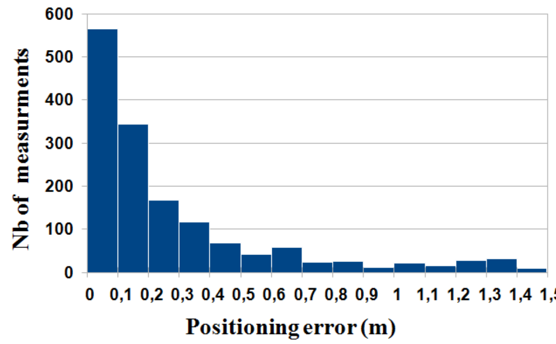

Fig. 5: Histogram of vision-based positioning errors. The error is the distance between the actual location of the user and the position estimated from the visual landmark.

Using the embedded GIS that contained geolocated positions of all the visual targets, we then retrieved the longitude and latitude of the landmark in Word Geodetic System coordinates (WGS84). Finally, from the geodetic coordinates of the object, its distance from the user, and the inverse of the heading, we computed the user’s coordinates in WGS84. Some tests have been made to verify the accuracy of the vision-based positioning (obtained from the visual landmarks only). The device was worn by a user in static position, in front of a visual target (4 different distances were evaluated: 2, 4, 8 and 10 meters). For each distance, the user rotated the head in all directions for sixty seconds in order to evaluate the accuracy and stability of the method. Across the different trials of 60 seconds duration, the object was detected about 1500 times, i.e. an average of 25 recognitions per second. Fig. 5 shows that 80% of the positioning errors were inferior to 50 cm and may hence provide accurate positioning and guidance for blind pedestrian. The observed error may reflect noise in the stereo-matching method, in the detection of the pattern-recognition algorithm, or in the head-tracking data.

Based on the two positions computed from GPS and vision, we finally estimated the user 2D position using a Bayesian framework based on a particle filter called Monte Carlo Localization (as proposed in [30], [31]). In this framework, the coordinates of building, rivers, walking areas, etc., provided by the GIS were used to constraint the particles generation and avoid incoherent positions. The implementation of this particle filter is still on progress, but we conducted a series of test experiments in different conditions (open-field areas with good GPS signals as well as degraded conditions in urban environment) with a first Kalman Filter fusing vision- and GPS- based positioning that showed promising results. All sensors, vision and GPS data was logged in order to constitute test sets. These data sets will be used in off-line simulations to assess the benefits of a particle filter combining vision and GPS, vs. a Kalman Filter based on GPS and Inertial Sensors, vs. GPS alone.

VI. Conclusion and Future Work

In this paper, we showed that existing EOAs for the Blind, usually based on commercial GPS and SIG are not adapted to Blind mobility; their major impediment being the lack of precision (10 to 20 meters in ideal condition). We presented a solution based on adapted SIG, and real-time fusion of A-GPS and embedded artificial vision positioning signals. The benefit of our device is two-fold: 1/ it provides an accurate positioning, compatible with Blind mobility and guidance; 2/ it matches the needs of Blind users in terms of space perception [32].

Our preliminary experiments demonstrate the feasibility of a GPS and vision-based assistive device for a blind pedestrian with the proposed architecture. The positioning module based on fusion is now being integrated in the NAVIG EOA prototype and will be tested in different environments to determine the gain in accuracy offered by the use of geolocated landmarks.

Though this approach was designed for assisted navigation for the visually impaired, we suggest that it is fully compatible with other situations requiring a precise positioning such as car navigation or robotic control where the use of cameras is already widely spread.

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