Detection and Tracking of an Explosives-Carrying Human with Odor-Sensor Based Multisensor Networks

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Abstract: - In this study, it is aimed to detect and track an explosives-carrying mobile human moving among other humans. To this aim, a least square estimation (LSE) based sensor and data fusion algorithm is developed to work in combination with a multisensor network consisting of odor, sound, and vibration sensors. The results are evaluated by simulations for various paths traveled by two humans, of which one carries an explosive. The simulation results demonstrate problems related to using odor sensors only and the improved performance in detection and path tracking obtained with the addition of sound sensors. The paper is the first reported study using odor sensors in combination with sound sensors for detection and tracking.

Keywords: - Odor sensors, multisensor networks, sensor/data fusion, least square estimation, detection and tracking

1 - Introduction

Although there is sufficient technology to detect metal weapons, detection of plastic explosives, such as C-4, with methods that are harmless to humans still remains to be a challenge. Metal detectors or X-ray facilities commonly used at airports and customhouses cannot find plastic explosives. Y-ray detection using irradiation of neutron beams is recognized as an effective method for C-4 detection at this point, but few actually use this method due to doubts about the safety of using nuclear radiation on the public. Hence, methods must be sought to carry out C-4 inspection safely, nondestructively, and without physical contact. One possible method is the use of THz radiation, which is claimed not to harm the human body in [1].

Detection of explosives using odor sensors is already in use for the detection of land mines and there has been ongoing research on odor sensor based detection of plastic explosives [2][3],[4],[5], which mostly develop ways to detect the different odorants in a specific odor.

The major contribution of this study is the development of a method that combines odor-sensors with other sensors for the detection and tracking of a human carrying an explosive while moving among several other mobile, unarmed humans. Unlike most studies, which aim detection of stationary explosives with the use of mobile sensors, in this study stationary sensor networks will be used to detect and track a mobile explosive. This approach will also increase the chances of tracking and disarming the intruder without his/her awareness and at an appropriate moment and will significantly limit the harm caused to innocent bystanders and security officers. The use of odor sensors will further contribute to optimize energy consumption in the network in that all sensor groups in the module will be kept on standby, unless a command is received from the odor sensor.

The structural diagram of the proposed sensor node is shown in Figure 1. Odor sensors detect the explosives while microphones serve as passive radars, which detect the location of mobile objects from their vibrations in the air. Accelerometers, used for the detection of seismic waves, could also be included to support vibration data coming from the ground. Finally, pressure sensors, which act upon direct contact, are proposed for calibration of the other sensors.

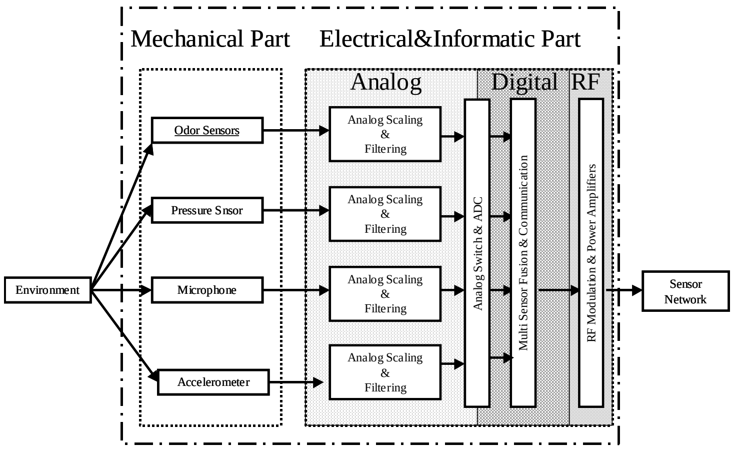

Figure 2: Structural diagram of proposed sensor node.

The odor sensor is comprised of a sensor array [6] to measure the density of a variety of odorants constituting an odor, and a classifier to fuse and classify the collected data [7]. This sensor detects the odor of the explosive, and estimates the source of odor [8]. Although the resolution of odor sensors is lower, their use in combination with other sensors for the approximate localization of the target proves to be very effective as demonstrated by simulations in this study.

This study is organized as follows; A brief introduction of current literature is given in Section 1, while detection and tracking models for sound sensors, pressure sensors and odor sensors are presented in Section 2, 3, and 4, respectively. Finally, simulation results and conclusions are presented in Section 5 and 6, respectively.

2 - Physical Model for Intruder Detection and Tracking using Sound Sensors and Accelerometers

Figure 2 gives a configuration example for the hub unit,the explosives carrying human (hereafter called the intruder) and random locations of the sensor modules as given in Figure 1. As will be demonstrated with the derived equations, the location of the intruder is determined with a minimum of 3 sound sensors, denoted by S_1, S_2, and S_3, the data from which is fused at the hub unit via Least Square Estimation (LSE). The hub unit in that sense is assumed to be just another sound sensor, which hears the intruder as soon as any one of the sensors sends it a signal. In the simulations, S1 is assumed to have heard the intruder first; hence, both S1 and hub unit are assumed to hear the intruder in dT seconds**.** As can be seen in Figure 1, the unknown distance between the hub unit and the intruder is denoted by d.

The derivation of the equations are based on the notation used in Figure 3. The coordinate axes of the hub unit is taken as reference; x,y are the coordinates of the intruder, while (x_1,y_1), (x_2, y_2) and (x_3, y_3) are the coordinates of S_1, S_2 and S_3, respectively.

Sound is a traveling wave of pressure and can be modeled as,

$$f(d,v,t) = K(t)\,f(t) \tag{1}$$

where f(t) is the sound signal and K(t) is an amplitude coefficient which decreases in time; v is the velocity of sound, which is approximately 332m/s in the air at 20°C.

At an arbitrary instant, t, an intruder appears within the range of S_1 at a distance, d_1 from S_1 as demonstrated in Figure 2. At different time instants, S_2 and $S_3 \ldots S_{50}$ also hear the intruder, with d_2 denoting the distance between S_2 and intruder, d_3 denoting the distance between S_3 and intruder, and so on... dT denotes the arrival time of the sound at S_1 and hence, at the hub unit. dT_{12} denotes the arrival time differences between S_1 and S_2; dT_{23} denotes the arrival time differences between S_1 and S_3. Note that dT is unknown, while dT_{12} , dT_{23} are measured.

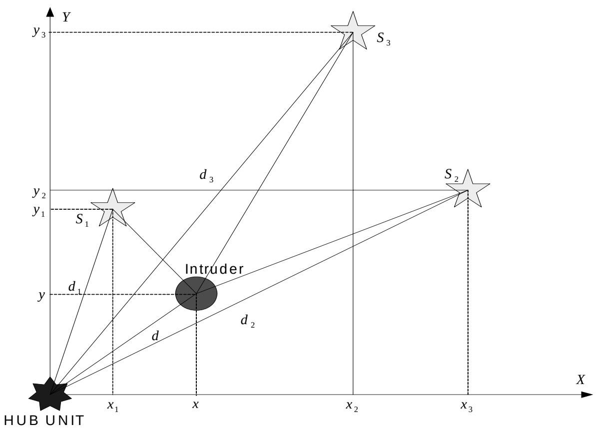

Figure 2: Configuration and definitions for intruder, sensors and hub unit

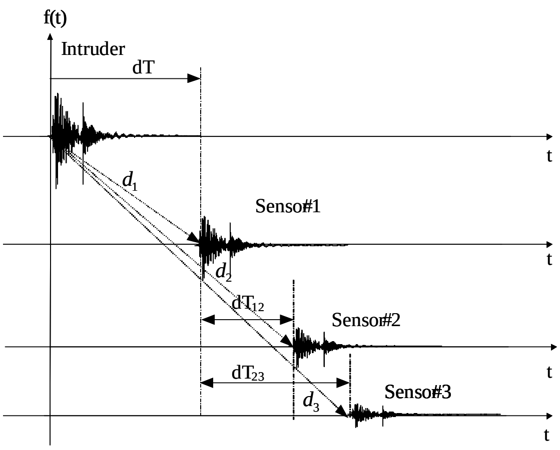

Figure 3: Intruder initiated sound waves with respect to sensors and hub unit

Base on these definitions, the following relationships can be derived:

$$\begin{aligned} d_1 &= v(dT)\,, \\ d_2 &= v(dT + dT_{12})\,, \\ d_3 &= v(dT + dT_{23}) \end{aligned} \tag{2}$$

Using (2), the following relationships can be given between each sensor and intruder coordinates:

$$(x-x_1)^2+(y-y_1)^2=(v(dT))^2 \quad (3)$$

$$(x-x_2)^2+(y-y_2)^2=(v(dT+dT_{12}))^2 \quad (4)$$

$$(x-x_3)^2+(y-y_3)^2=(v(dT+dT_{23}))^2 \quad (5)$$

Combining (3) with (4), (6) is obtained, while (3) and (5) yield (7), and (4) and (5) yield (8).

As can be seen from the equations, x,y, and dT are the unknown variables, while all terms on the right are known. Hence, it can be seen that determining the intruder's location in the 2-dimensional space requires 3 sensors, while 3-dimensional space would require a minimum of 4 sensors. At this point, to reflect the more realistic nature of sound velocity, v, which is actually dependent on the material and temperature, a white noise is added to the above equations and the solution is sought in terms of a Least Square Estimation problem.

2 - Physical Model for Intruder Detection and Tracking using Pressure Sensors

Each module has a pressure sensor operating as logic sensors. In the experiments, they will be activated upon stepping and hence, serve as a calibrator for the other sensors and detection/tracking algorithm; however, in the simulations, these sensors are assumed to be activated when the intruder comes within a very close range of that certain point representing the sensor module. For example, in the presented simulation results, only S_5 (sensor 5) was stepped on.

3 - Preliminary model for odor diffusion and measurement

Further assumptions in the simulations are that the explosives are emitting a gas constantly, which gives rise to a certain gas density at every instant, t, and this gas disperses into the environment by diffusion. Hence, a gas starting to disperse into the environment at t_1, will lose its effect in time but will exist forever. From the following instant, t_2 and on, new gas amounts will be effective cumulatively at any given point (or sensor module) in the environment.. The new gas amount will also disperse into the environment via diffusion, but with a reduced effect as time advances. Each odor sensor senses and measures the cumulative gas amount at that point

Since Fick´s 2nd law is a partial differential equation with only a few analytical solutions available for special cases, numerical methods have to be used to apply it to technical problems. An analytical solution of Fick´s 2nd law is given by Equation (12): [9]

$$c(t,d)=c_\Gamma.erfc\left(\frac{d}{2\sqrt{Dt}}\right) \quad (12)$$

where c: dispersed gas amount, c_Γ : gas amount at source, d: distance from source, D: constant. In the simulations, odor is considered as a gas dispersing in amounts of Δc at every t. As the explosive-carrying human moves, at every point he/she moves at an new instant t, a new gas source, c_Γ starts its dispersion based on (12). A given odor sensor in the environment located at a distance, d from the intruder will accumulate n gas amounts, from n c_Γ sources, giving rise to a gas amount, S_i as expressed below:

$$S_i=\sum_{k=1}^{n}c_k(t,d) \quad (13)$$

Although a fusion and ANN based decision algorithm will be conducted for the multiple odor sensors in one module, only one odor sensor per module is considered in the simulations. Hence, for the determination of the coordinates for the explosive-carrying intruder, a weighted-average is performed combining the measured S_1, S_2, S_3, ...amounts collected from all odor sensors (50 in this case) at coordinates x_1, y_1, x_2, y_2, x_3, y_3... to determine the explosive-carrying intruder's coordinates, x and y.

$$y=\frac{\sum S_iY_i}{\sum S_i}$$

$$x=\frac{\sum S_iX_i}{\sum S_i} \quad (14)$$

$$2(x_2-x_1)x+2(y_2-y_1)y+2v^2(dT_{12})dT=-v^2dT_{12}^2-x_2^2-y_2^2+x_1^2+y_1^2 \quad (6)$$

$$2(x_3-x_2)x+2(y_3-y_2)y+2v^2(dT_{23}-dT_{12})dT=-v^2dT_{12}^2+v^2dT_{23}^2-x_3^2-y_3^2+x_2^2+y_2^2 \quad (7)$$

$$2(x_1-x_3)x+2(y_1-y_3)y+2v^2(dT_3)dT=v^2dT_{23}^2-x_1^2-y_1^2+x_3^2+y_3^2 \quad (8)$$

$$2(x_2-x_1)x+2(y_2-y_1)y+2v^2(dT_{12})dT+\varepsilon_1=-v^2dT_{12}^2+x_2^2+y_2^2-x_1^2-y_1^2 \quad (9)$$

$$2(x_3-x_2)x+2(y_3-y_2)y+2v^2(dT_{23}-dT_{12})dT+\varepsilon_2=-v^2dT_{12}^2+v^2dT_{23}^2+x_3^2+y_3^2-x_2^2-y_2^2 \quad (10)$$

$$2(x_1-x_3)x+2(y_1-y_3)y+2v^2(dT_{23})dT+\varepsilon_3=-v^2dT_{23}^2-x_1^2-y_1^2+x_3^2+y_3^2 \quad (11)$$

As the simulation also considers more than one human (without explosives) in the environment, the distinction of a "different human" is made by evaluating the traveled distance in the expired time interval in terms of its feasibility for a human-being. The same approach is applied for the determination of coordinates using the sound and pressure sensors.

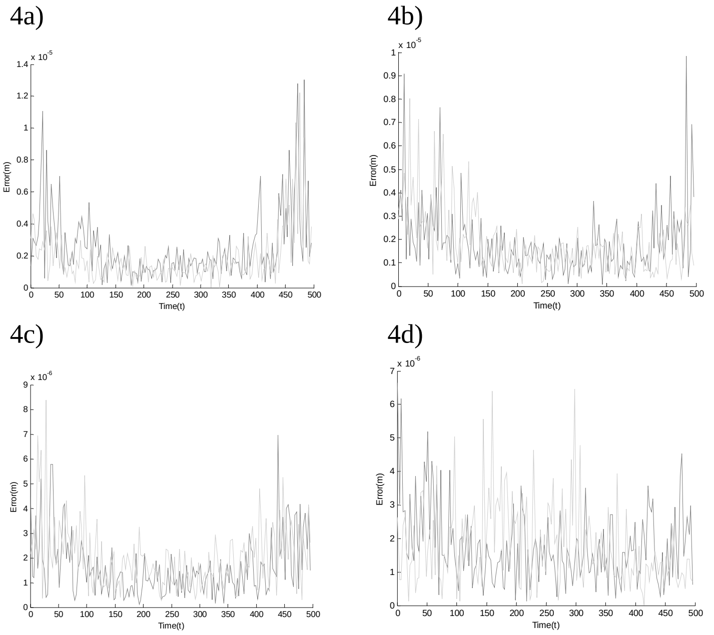

Figure 4: Tracking Error in Each trajectories

4 - Simulation Environment

In the simulation, a hub unit and randomly deployed fifty sensor modules are considered in a 10 by 10 square meter area. The area is assumed to have no air draft, no boundaries, hence no reflection effects. The environment temperature and the velocity of sound throughout the simulations are assumed to be constant. It is also assumed that the 2 humans (one carrying explosives) are emitting sound waves periodically.

In this study, it is also assumed that the location of each sensor module and hub unit is known. Each module in the 50-sensor network consists of an odor sensor, microphone, accelerometer and pressure sensor. In this simulations, due to the similarities of their physics, sound sensors and accelerometers are assumed to have the same model.The total simulation time is 50 seconds, with the sampling times for sound/pressure/ accelerometers taken as 100 μsec and that of odor sensors (with a slower response) taken as 1 sec. In these results, data fusion is performed using a Least Square Estimation algorithm, which fuses all odor signals and motion signals separately combining data coming from sensors of the same type. However, a decision-making process which evaluates odor and motion signals together is also performed in determining the motion of the "mobile" explosive and separating it from the trajectory of the unarmed human.

5 - Simulation Results

The first group of simulation results is derived for tracking of two humans, only based on fused data from sound sensors, accelerometers and pressure sensors. Figure 4(a) depicts the performance of the algorithm in terms of tracking error or deviation between the actual and calculated paths of the two humans walking in spinal trajectory, walking in parallel straight lines in Figure 4(b), crossing each others' paths in Figure 4(c) and Figure 4 (d).

Second group of results presents the performance of the odor sensor based algorithm, which is used to distinguish the explosive carrying human from the innocent one. In the figures, the *'s indicate the location of the sensor modules; the light grey triangles represent the estimated trajectory of the innocent human and dark grey triangles represent that of the explosive-carrying human; finally the black circles indicate the trajectory of the "mobile"explosive estimated based on data collected from the odor sensors only. Figure 5 (a) represents the performance of the algorithm fusing data from odor sensors with the other sensors in case of spinal paths. It can be noted that the algorithm detects and tracks the intruder quite well. The performance of the algorithm is also observed to be adequate in Figure 5(b), where the two humans are walking in parallel, and in Figure 5(c) and (d), where the paths cross.

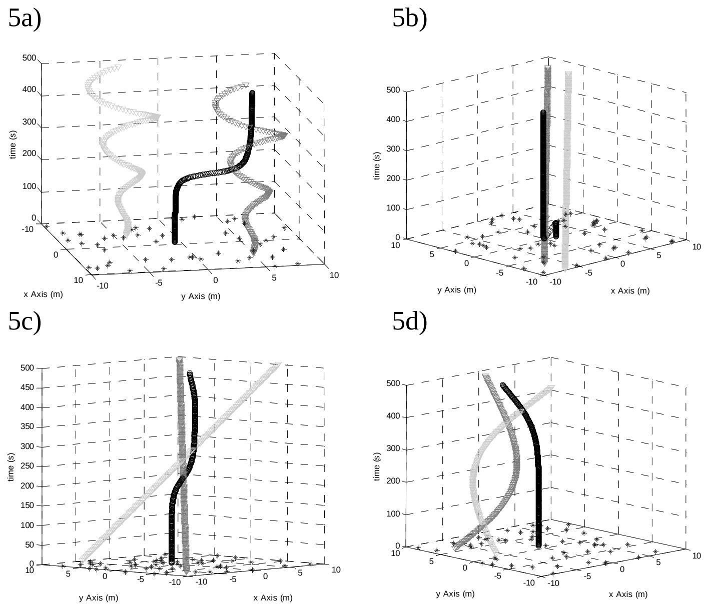

Figure 5: Simulation of the system by various trajectories.

6 - Conclusions

The simulation results support the expectation that sound sensors and accelerometers are more effective in tracking mobile objects due to their fast response; on the other hand, odor sensors are obviously very effective in "detecting" the odor, but due to their slow response, they should be used in combination with sound/vibration sensors to improve the "tracking" performance.

Moreover, in a noisy environment, accelerometers could effectively assist the sound sensors. Non-uniformities of the ground are very effective on the performance of accelerometers; hence, sound sensors could be more efficient in such cases. Velocity of sound depends on ambient temperature, hence could benefit from calibration. Pressure sensors could serve this purpose. Pressure sensors have high accuracy, but low possibility of being activated. Therefore, it can be concluded that sensor/data fusion of all the above mentioned sensors is necessary to increase accuracy and robustness of the system.

With the developed algorithm, it is possible to detect and track the target using data gathered from a minimum 3 sensors of the same type. However, using data also from different sensor types helps distinguishing the target from other interfering sources in the environment. With information obtained by fusing the data from each different sensor type, it is possible to exclude data that is not in harmony with data collected on the target. Hence, fusing the data coming from each sensor in the sensor modules with a scaling factor helps increase "target" detection and tracking. The evaluation of the multiple sensor data in relation to the odor sensor data is essential in the accurate tracking of the "mobile' explosive in this study. Odor sensors are not only capable of the initial detection of the explosive, but also capable of serving as a somewhat slow guide in relating the detected odor to the possible trajectories with the help of the other sensors, as observed in the simulation results. Logic data coming from pressure sensors will act as a calibrator for position determination and contribute to accuracy. Odor sensor based network activation may also give rise to reduced energy consumption in the network

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