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A Motion-Tracking Ultrasonic Sensor Array for Behavioral Monitoring

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Abstract

The application of Kalman filtering to track subjects' movements during a behavioral experiment is discussed. Specifically, an overhead array of wireless, ultrasound sensors automatically tracks the position of a parent, child, and stranger over a $4.45 \text{ m} \times 4.23 \text{ m}$ observation area. This *WiPsy* (Wireless sensors for Psychology research) system provides accurate, real-time quantitative metrics for psychological evaluation in lieu of traditional qualitative manual coding. Moreover, tracking subjects using ultrasound sensors is less error-prone than existing methods that track based on human coding of video. In particular, the Kalman filter, which forms the core of this tracking system, can locate targets with a mean square error of about 1.3 m^2 . Overall, *WiPsy* strives to streamline data acquisition, processing, and analysis by providing previously unavailable assessment parameters.

Index Terms

image array; Kalman filter; sensor network; ultrasound

I. Introduction

Human behavior has important significance across many levels of functioning including the organism level, the psychological level, and the relational level. At the organism level, behavior serves to promote survival through accessing basic needs. At the psychological level, behavior may satisfy a need or motivation aimed at satisfying emotional needs. At the relational level, behavior guides an individual through a social world. Thus, the quantification of human behavior has ramifications for better understanding people across many levels of analysis. This behavioral analysis is primarily limited to human subjective ratings and laboratory assessments. Endless possibilities exist by quantifying behavior and exporting it to contexts beyond the lab. This research bridges this gap by developing a sensor network that allows for online data processing. The previously expensive and time consuming process of human coding is replaced with more accurate, quantitative measurements.

In this research, a sensor network is developed to assess young children during interactions with their mothers. During infancy, the mother is regarded as a “secure-base” from which the infant explores and habituates to the outside environment. In times of safety and security, the infant feels free to investigate his surroundings in attempts to understand and master his environment. Under threatening or distressful conditions, the infant returns to the mother for soothing comfort and protection. Thus, the mother is the base from which the infant derives comfort and explores. Attachment researchers regard the child’s use of distance negotiation with the mother, under conditions of both safety and threat, as an important indicator of the quality of the mother-infant attachment bond [1]. For over thirty years, the distances between the child-parent and child-stranger pairs have been assessed by trained human coders. The coding process is unsatisfactorily qualitative and tediously slow. The system described in this paper replaces human coding with a wireless array of ultrasound sensors. The ultrasound data is processed in real time through a tracking filter, which extracts the positions of the child, parent, and stranger and displays the child-parent and child-stranger distances. This gives researchers the ability to assess human behavior instantaneously.

The system architecture is described in Section II. A summary of the experimental results and the psychological analysis is given in Section III. Final remarks are made in Section IV.

II. System Architecture

The complete system architecture consists of two major components: the imaging subsystem and the tracking subsystem. The former is composed of an overhead array of 6×6 Tmote Sky motes, each equipped with a set of Devantech SRF05 ultrasonic transmitter/receiver transducers. The array transmits all echo measurements via wireless communication to a base station, which assembles and displays a real-time image of the room using Matlab. This data is also fed into a tracking filter, which estimates the positions of three possible targets within the room. Once positions are determined, the child-parent and child-stranger distances are computed and displayed.

Instead of using conventional wired communication, the imaging system relays information over a wireless channel as an investigative procedure to determine whether fading channels have sufficient bandwidth for conveying real-time ultrasound images. Future work will include a means to easily deploy a movable, battery-operated version of the array into homes for *in situ* monitoring.

Conventional wireless sensor networks often require a device be placed onto each tracked target [2], [3]. Such systems include Olivetti Research’s Active Badge [4], AT&T’s Active Bat [5], Microsoft’s RADAR [6], MIT’s Cricket [7], and Ascension’s MotionStar [8]. However, this imaging system must avoid using tracking tags on targets because children are often unwilling to wear them. Attempts to attach such tags result in the child’s noncooperation or a forced tag removal midway through the experiment. To circumvent this limitation, the imaging system is set up as a large-scale ultrasonic array akin to conventional ultrasonic arrays used in fetal imaging. In essence, the ultrasonic array takes snapshots of the room without requiring targets to wear specialized tracking devices.

Other tracking systems that also do not require the wearing of tracking tags are computer vision systems [9], [10]. However, those systems suffer from larger processing requirements and possible occlusion problems [2]. This system requires comparatively less computation and avoids most occlusion situations.

A. Mote Development Environment

The Tmote Sky motes are programmed using the TinyOS development environment. TinyOS version 2 is chosen for its high resolution timers. These 32 kHz clocks enable the ultrasound sensors to provide a vertical height resolution of approximately 1 cm. However, in practice, these clocks are empirically slowed down by a factor of 20, which corresponds to a vertical resolution of about 20 cm. The justification for this reduced clock speed is simply to give the microprocessor sufficient CPU time to perform required computations (such as checking the radio for received packets) instead of being inundated with processing timer triggers. Since the smallest subjects, 18-month old children, typically have heights around 80 cm [11], this decreased resolution does not affect the system's detection ability.

B. Sensor Array

Attached to each ceiling-mounted mote is a downward-facing ultrasound sensor, shown in Figure 1. When signaled by the mote, the sensor emits an 8-cycle, 40 kHz ultrasound pulse. This directed pulse returns to the detector after being reflected off either the floor or an interposed object. The flight time of the pulse gives the range to the closest object below the sensor. Usually, this object is a subject's head, a chair, a toy on the floor, or the floor itself.

By arranging a 6×6 grid of these ultrasound sensors (shown in Figure 2), an image of the 4.45 m×4.23 m observation room can be taken. Locations of targets of interest are extracted from this image using peak detection. The sensor array is capable of discerning two adults separated by at least 73 cm. Objects separated by less than this minimum distance will appear to the imaging system as a single entity.

C. Tracking Filter

Because of the poor lateral resolution of these ultrasound images, multiple, closely clustered targets appear as a single peak instead of as separate individuals. To circumvent this problem, a tracking filter is implemented to estimate the subjects' positions when the imaging system is unable to resolve all targets.

The Kalman filter is chosen over other linear filters because of its simplicity. This filter optimally minimizes the mean square error (MSE) between a set of noisy measurements and some (noiseless) state space variables, assuming the state variables form a Markov chain. Some advantages with using a Kalman filter over a Wiener filter are the former's causal nature and its ability to handle non-stationary processes [12], [13]. Therefore, the Kalman filter can be used for real-time tracking and imposes few assumptions about the data's behavior.

The vector Kalman filter implemented in this system assumes that the state space variable $\mathbf{s}[n]$ at current time n evolves according to the linear, time-invariant, Gauss-Markov model given by (1), where $\mathbf{A}$ is the state transition matrix defined in (12) and (13). The driving term $\mathbf{u}[n]$ is assumed to be white, Gaussian noise with zero mean and covariance $\mathbf{Q}$. The 18×18 matrix $\mathbf{Q}$ is diagonal with diagonal variance entries specified by $(0, \sigma_u^2, 0, 0, \sigma_u^2, 0, 0, \sigma_u^2, 0, 0, \sigma_u^2, 0, 0, \sigma_u^2, 0, 0, \sigma_u^2, 0)$. The value $\sigma_u^2=0.001$ is chosen to tune the filter such that tracking exhibits smooth behavior.

$$\mathbf{s}[n] = \mathbf{A} \cdot \mathbf{s}[n-1] + \mathbf{u}[n] \quad (1)$$

Specifically, the state variable $\mathbf{s}[n]$ of three tracked targets is defined as the 18-element column vector:

$$\mathbf{s}[n] = [\mathbf{s}_1[n] \ \mathbf{s}_2[n] \ \mathbf{s}_3[n]]^T \quad (2)$$

$$\mathbf{s}_i[n] = \begin{bmatrix} x_i[n-1] & x_i[n] & v_{i,x}[n] & y_i[n-1] & y_i[n] & v_{i,y}[n] \end{bmatrix} \quad (3)$$

where $(x_i[n], y_i[n])$ is target i 's location at time n and $v_i[n]$ is the target's velocity also at time n . The velocity is included in the state variable as an auxiliary variable. The observation vector $\xi[n]$, given by (4), retains only the current target positions because the observation matrix $\mathbf{H}$ is constructed to be diagonal with diagonal entries given by (0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0). The additive noise $\mathbf{w}[n]$ is white and Gaussian with covariance matrix $\mathbf{C}$, which is defined in (10) and (11).

$$\xi[n] = \mathbf{H} \cdot \mathbf{s}[n] + \mathbf{w}[n] \quad (4)$$

In (5), the estimate $\hat{\mathbf{s}}[n|n]$ of the state variable at time n , given all past observations through and including those at n , is computed using the prediction vector $\hat{\mathbf{s}}[n|n-1]$, the Kalman gain vector $\mathbf{K}[n]$, the minimum prediction MSE matrix $\mathbf{M}[n|n-1]$, and the minimum MSE matrix $\mathbf{M}[n|n]$. All of the previous quantities are either given or can be computed recursively from (6), (7), (8), and (9):

$$\hat{\mathbf{s}}[n|n] = \hat{\mathbf{s}}[n|n-1] + \mathbf{K}[n] (\xi[n] - \mathbf{H} \cdot \hat{\mathbf{s}}[n|n-1]) \quad (5)$$

$$\hat{\mathbf{s}}[n|n-1] = \mathbf{A} \cdot \hat{\mathbf{s}}[n-1|n-1] \quad (6)$$

$$\mathbf{K}[n] = \mathbf{M}[n|n-1] \cdot \mathbf{H}^T (\mathbf{C} + \mathbf{H} \cdot \mathbf{M}[n|n-1] \cdot \mathbf{H}^T)^{-1} \quad (7)$$

$$\mathbf{M}[n|n-1] = \mathbf{A} \cdot \mathbf{M}[n-1|n-1] \mathbf{A}^T + \mathbf{Q} \quad (8)$$

$$\mathbf{M}[n|n] = (\mathbf{I} - \mathbf{K}[n] \cdot \mathbf{H}) \mathbf{M}[n|n-1] \quad (9)$$

where $\mathbf{I}$ is the identity matrix [12]. The column vectors $\mathbf{s}[n]$, $\mathbf{w}[n]$, $\xi[n]$, and $\hat{\mathbf{s}}[n|n]$ all have size 18×1 . The square matrices $\mathbf{H}$, $\mathbf{C}$, $\mathbf{K}[n]$, $\mathbf{M}[n|n]$, and $\mathbf{I}$ all have size 18×18 . The forward recursion is initiated using $\hat{\mathbf{s}}[0|0] = [110110110110110110]$ and $\mathbf{M}[0|0] = \mathbf{C}$. That is, the initial state assumes that all targets are stationary and start at the door, which is located at (1,1).

In the Kalman filter, it is assumed that each target's x - and y -locations operate independently and that all three targets move mutually independently over short time durations (long-term location correlations may still exist). Given these independence assumptions, the covariance matrix $\mathbf{C}$ and the state transition matrix $\mathbf{A}$ are quite sparse:

$$\mathbf{C} = \begin{bmatrix} \mathbf{c} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{c} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{c} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{c} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{c} \end{bmatrix} \quad (10)$$

$$\mathbf{c} = \begin{bmatrix} \sigma_c^2 & 0 & 0 \\ 0 & \sigma_c^2 & 0 \\ 0 & 0 & 2\sigma_c^2 \end{bmatrix} \quad (11)$$

$$\mathbf{A} = \begin{bmatrix} \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{a} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{a} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{a} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{a} \end{bmatrix} \quad (12)$$

$$\mathbf{a} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & \Delta t \\ -\frac{1}{\Delta t} & \frac{1}{\Delta t} & 0 \end{bmatrix} \quad (13)$$

where $\sigma_c^2=1$, $\Delta t = \frac{1}{\text{frame rate}} = 1$ s, and the $\mathbf{0}$ entries in frame rate $\mathbf{C}$ and $\mathbf{A}$ are 3×3 matrices of zero.

Internally, the Kalman filter assumes that targets move in a straight line over two consecutive time samples. Therefore, the state transition matrix $\mathbf{A}$ predicts a target's current location based on its previous position and velocity, and determines the target's new velocity from the current and previous positions. Position measurements older than two samples are not used to calculate velocity to allow flexibility for fast-changing velocities. Notably, this occurs when a target alters direction or speed, which breaks the rectilinear motion assumption.

The ultrasound sensors give height information of objects in the experiment. This peak information must be pre-processed from height information into position information. In particular, this pre-processing step must determine which of the largest peaks correspond to each target and order the respective entries into the observations $\zeta[n]$. Beyond having the positions and heights of peaks, the preprocessor also knows time information and can also access the immediately previous observation $\zeta[n-1]$. Based on correlations in peak heights, correlations in position history, and the number of expected targets in each epoch, it must fuse this information to create ordered tuples for input into the Kalman filter. Indeed, this pre-processing decision tree forms the bulk of the "intelligence" for the tracking system. The Kalman filter itself merely smooths over any noise present in the system.

Additional system design challenges, including power, noise, and speed tradeoffs, can be found in [14]. Relevant specifications for the sensor and the array are summarized in Table I.

III. Results

A. Array Performance Metrics

A total of 168 experiments are performed on child-parent pairs drawn from varied socio-economical and educational backgrounds. In each experiment, the ultrasound sensor information is supplemented with video recorded by a conventional video camera system. Based on the latter, trained psychologists manually estimate the positions of child, parent, and stranger by observing each target's placement relative to a grid marked on the floor. This "coded" data serves as the ground truth for all target positions. The novel presence of the floor grid validates this coded data as the "gold" standard for the truth comparison. Previous assessments in other behavioral experiments have no such grid and are far more error-prone.

A representative frame of the ultrasound video captured during the experiment is shown in Figure 3. All frames are bilinearly interpolated to increase the image resolution from 6×6 square pixels to 21×21 square pixels.

Figure 4 compares a typical Kalman-filtered estimate of the targets' positions against their respective ground truths. As a performance metric, the ensemble mean square error between the Kalman-estimated and "true" positions appear in Table II. It is unsurprising that the largest errors occur in estimates of the child's position because the child's role is mainly unscripted. Free-roaming children yield the noisiest data measurements because they least obey the motion assumptions programmed into the tracking filter. However, the relatively low errors with tracking parents and strangers are expected because their roles are thoroughly scripted and their freedom of movement is more restricted. Thus, the tracking system can estimate their movements more accurately. From these position estimates, the child-parent and child-stranger distances can be easily computed with the standard distance formula. Finally, these calculated distances are further processed by psychologists using higher-level statistical analyses described in Section III-B.

B. Psychological Application

The distance data captured during this study are used in a psychological study to examine whether children's ability to utilize their mother as a secure base during a stressful laboratory paradigm is associated with their ability to modulate physiological distress. To expand understanding of physiological processes in association with child distress, the present study focuses on examining autonomic nervous system (ANS) indices of distress and looks at the relationship between indices of distress and the distance between child and mother. The selection of this specific stress-response system is guided by evidence that the ANS is primed in the context of stressful interactions [15], [16]. Specific focus is made on activity within the sympathetic nervous system (SNS). The SNS reflects the first wave of autonomic response to stressful events. During times of challenge and threat, the SNS primes the body for fight/flight response by increasing cardiac output, oxygen flow, and blood glucose levels [17], [18]. This physiological indicator of ANS function has been implicated as a possible pathway in models exploring the impact of stress and challenge on physical [19] and psychological [20], [21] well-being.

In each of the 168 experiments, mothers and children participate in the Strange Situation paradigm (SSP) [22]. The SSP has been used in previous research exploring mother-child relationships and has proven a meaningful index of children's arousal to stressful situations [23]. The standard paradigm is conducted as described in [22] and [1]. The SSP consists of seven episodes, each of which lasts for three minutes. These episodes are:

1. Mother and child enter the paradigm room in which there are various toys and two bean-bag chairs.
2. A stranger enters the room and sits in a chair directly across from the mother. The stranger remains silent and nonresponsive for one minute, then engages the mother in conversation during the next minute, and then attempts to engage the child in play during the final minute.
3. Mother exits the room, leaving behind her child and the stranger
4. Mother calls out to her child two times from outside the room and re-enters. Shortly thereafter, the stranger discretely exits.
5. Mother exits again, leaving her child alone in the room.
6. Stranger re-enters the room.
7. For a second time, the mother calls to her child two times from outside the room and then re-enters.

During the SSP, children's ECG signals are recorded using Alive Heart Monitors from Alive Technologies Pty. Ltd. [24]. This platform allows real-time monitoring of a child's ECG activity without tethering wires to a base station. Thus, children are able to freely move about the room while having their ECG signals recorded. The ECG monitor uses a precordial, two-pole electrocardiogram lead on the chest. Data from these leads are fed into a portable unit strapped to the child and locally stored on an SD card. The ECG signal is sampled at 300 Hz and has a voltage range of -2.5 V to 2.5 V. Power spectral analysis of the inter-beat interval (IBI) time series across the laboratory session is used to quantify activity within the sympathetic nervous system [25], [26]. The power spectrum contains a low-frequency (0.04 Hz to 0.15 Hz) component [26]. Power in this spectral band reflects the influence of the sympathetic branch on the heart. It is hypothesized to be an indicator of physiological response, where higher values indicate higher sympathetic activation [20].

Results are presented in a correlation matrix in Table III. This data illustrates that as distance between children and mothers decrease, children's sympathetic activities also decrease. That is, the findings show that the child-mother distance correlates with children's ability to successfully use their mother as a source of comfort and support. In the first separation episode, the average child-mother distance is not associated with sympathetic activation. This may be an artifact of the paradigm structure. After the first separation from the mother, a female laboratory assistant is still present in the room with the child. Thus, children may not have found their mother's separation to be particularly distressing. In fact, the paradigm is structured to gradually increase distress in the child. This first separation, coupled with the presence of another female adult, is shown to not be inherently stressful to many children. In the first reunion episode, overall distance from the mother is associated with lowered child sympathetic arousal.

In the second separation episode, there is now an association between average distance from mother and children's sympathetic arousal. In this episode, the mother leaves the room and the child is completely alone. This act is typically very distressing to children. In the final reunion episode, lower average distance from the mother is associated with lower sympathetic arousal in the child, suggesting that children are able to better reduce their distress.

IV. Conclusion

The developed sensor array replaces human-coded behaviors with automatic and accurate measurements in a laboratory setting. However, this system has extensive application

possibilities beyond the lab including unobtrusive monitoring of human movement in hospital, work, and home environments. For example, aging populations could be tracked and monitored within their home to determine whether falls have occurred and medical intervention is necessary. Applications of this sensor network could improve our ability to track, assess, and intervene in human functioning across a multitude of settings.

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Biographies

Roland Cheng received the B.S. degree in 2006 from the Department of Computer Science, the B.S. and M.S. degrees from the Department of Electrical and Computer Engineering, in 2006 and 2007, all from the University of Rochester, Rochester, NY, where he is currently pursuing the Ph.D. degree.

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She is an Associate Professor in the Department of Electrical and Computer Engineering at the University of Rochester, Rochester, NY, and she holds a secondary appointment as an Associate Professor in the Department of Computer Science. She also currently serves as Dean of Graduate Studies for Arts, Sciences and Engineering at the University of Rochester.

Her current research interests lie in the areas of wireless communications and networking, mobile computing, and multimedia communication.

Dr. Heinzelman received the NSF CAREER award in 2005 for her research on cross-layer architectures for wireless sensor networks, and she received the ONR Young Investigator Award in 2005 for her work on balancing resource utilization in wireless sensor networks. She is an Associate Editor for the IEEE TRANSACTIONS ON MOBILE COMPUTING, an Associate Editor for the ACM Transactions on Sensor Networks and an Associate Editor for Elsevier Ad Hoc Networks Journal. Dr. Heinzelman is a senior member of the ACM, and she is co-founder of the N² Women (Networking Networking Women) group.

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Dr. Sturge-Apple earned a M.Ed. from Harvard University in the area of Risk and Prevention, and worked as a family counselor for five years. After this, she returned to school and received her Ph.D. in Developmental Psychology from the University of Notre Dame and served as a post-doctoral fellow at the Mt. Hope Family Center. Her research focuses on understanding family processes, child coping and adaptation to family contexts, and children's socio-emotional adjustment.

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Zeljko Ignjatovic received the B.S. degree in electrical engineering from University of Novi Sad, Serbia, and the M.S. and Ph.D. degrees in electrical engineering from University of Rochester, NY in 1999, 2001, and 2004, respectively.

He is currently an Associate Professor of Electrical and Computer Engineering at University of Rochester. His areas of interest include analog circuit design and development of A/D converters, image sensor architectures, radar and ultrasound imaging techniques and related signal processing methods.

Fig. 1.
Ceiling-mounted mote with attached ultrasound sensor.

Fig. 2.
Worm's eye view of 6×6 array of motes.

Fig. 3.
Ultrasonic image of child, parent, and stranger in observation room (bird's eye view).

Fig. 4. Estimated position of targets compared to ground truth. Red is the x-direction and blue is the y-direction. The solid line is the Kalman estimated positions, and the dots are the ground truth.

TABLE I

Sensor and array specifications

	Specification	Nominal	Actual
sensor	half-power beamwidth	40°	-
	power supply	5 V	3 V
	max detectable distance	4 m	2.1 m
	resolution in propagation direction	-	20 cm
array	resolution in azimuth plane	-	73 cm × 73 cm
	sensor separation	-	61 cm × 61 cm
	observation area	-	4.45 m × 4.23 m

TABLE II

Ensemble mean square errors of estimated target positions

Target	MSE _x (m ²)	MSE _y (m ²)
Child	1.521	2.515
Parent	0.607	1.581
Stranger	0.571	0.859

TABLE III

Correlation matrix between mother and child distances

Variables	1	2	3	4	5
1. Distance from mother	1	-	-	-	-
2. SNS during first separation	0.01	1	-	-	-
3. SNS during first reunion	0.34*	0.03	1	-	-
4. SNS during second separation	-0.31*	0.43	0.04	1	-
5. SNS during second reunion	0.41*	0.14	0.23*	0.17*	1

* probability of error < 0.05