ChatGPT

Cognitive-Effort Cube Model: Bridging Movement Psychology and Computational Analysis

Introduction

Movement psychology seeks to explain how internal cognitive states and intentions manifest in the dynamics of physical movement. A key insight from Rudolf Laban's work is that movement *quality* – the *how* of movement – reflects "inner intent or motivation behind a movement" [1]. Building on this foundation, the **cognitive-effort cube model** integrates cognitive processes with movement dynamics (effort qualities) in a structured way. In this model, fundamental cognitive spectrums (Deciding, Attending, Intending, Adapting) correspond to Laban's Effort factors (Weight, Space, Time, Flow) [2], and their binary combinations give rise to distinct *working actions*. This essay establishes the theoretical underpinnings of the cognitive-effort cube model, defining its key concepts and showing how it provides a bridge to computational analysis of movement. We will define the cognitive spectrums and their polarities, the "externalized drives" (Doing, Spell, Passion, Vision) that combine these spectrums, and the notion of inner attitudes. We then introduce the cube model of working actions, illustrating how each action arises from a unique combination of cognitive qualities linked to classical effort qualities (e.g. Quick vs. Sustained, Direct vs. Flexible, Strong vs. Light). Finally, we discuss how movement – especially human gait – can be quantitatively modeled using rhythm and frequency as proxies for cognitive intention, and how 3D skeletal data (from tools like MediaPipe or MotioNet) can be transformed into frequency profiles that map onto our theoretical constructs. A brief code example demonstrates parsing motion data into such profiles and classifying them into working actions. Throughout, we make the case that this cognitive-effort cube model provides a rigorous yet practical framework to connect movement psychology theory with machine learning and motion classification systems in AI.

Cognitive Spectrums and Effort Qualities

Cognitive spectrums refer to four internal processes or modes of attention that influence movement: **Deciding, Attending, Intending,** and **Adapting**. These can be thought of as intrinsic attitudes or mindset dimensions that correspond to Laban's four Effort factors:

- **Deciding** – the spectrum of determination or commitment behind actions. This aligns with the *Weight Effort* quality, ranging from *Light* to *Strong* [2]. A "light" attitude implies delicacy or tentativeness in one's decisions and movements, whereas a "strong" attitude reflects firm commitment and forceful execution. In movement terms, Weight Effort indicates the force or pressure exerted: *strong* movements feel forceful and resolute, while *light* movements feel gentle or hesitant [2]. Thus, *Deciding* (inner resolve) is outwardly manifested by the weight of movement – a decisive person may move with firmness (strong weight) versus an undecided or yielding person who moves lightly.

- **Attending** – the spectrum of focus or attention to the environment. This corresponds to the *Space Effort* quality, which ranges from *Direct* to *Indirect (Flexible)* [3]. A *direct* attention means a single-focused, targeted approach (moving in a straight, clear path toward a point of interest), whereas *indirect* (or flexible) attention involves scanning, multi-focused awareness and an adaptable path. In movement, Direct vs. Indirect Space Effort describes the clarity of the movement's path – direct movements have a clear, linear focus, while indirect movements meander or pivot as if attending to multiple cues [3]. Thus, *Attending* cognitively (how one gathers information or concentrates) shows up as the spatial focus of movement.

- **Intending** – the spectrum of urgency or tempo of one's intention. This maps to the *Time Effort* quality, ranging from *Sustained* to *Sudden (Quick)* [2]. A *sustained* intention implies patience, extended deliberation and lingering pace, whereas a *quick* intention implies urgency, immediacy and abrupt pace. In movement terms, Time Effort reflects speed and acceleration: *sustained* movements are slow, smooth, drawn-out, while *sudden/quick* movements are rapid, with bursts of acceleration [2]. Thus, *Intending* (the internal time-pressure one feels to act) becomes visible in whether one moves in a leisurely sustained manner or with quick urgency.

- **Adapting** – the spectrum of flexibility versus control in one's approach. This aligns with the *Flow Effort* quality, ranging from *Free* to *Bound* [4]. *Free flow* represents fluid, unrestrained movement, readily adapting and going with the "flow" of impulses or environment, whereas *bound flow* represents controlled, contained movement, carefully regulated and resisting spontaneous change [4]. Adapting is thus the inner attitude of openness to change versus tight regulation. A person high on adapting (free flow) moves with continuous, unbroken motion and easily adjusts their motion, whereas someone low on adapting (bound flow) exerts inner control that manifests as restrained, stop-and-go or taut movement. Flow Effort has to do with *continuity and control* – free flow feels released and fluid, bound flow feels tight and controlled [4].

These four cognitive spectrums are essentially **inner attitudes** toward each motion factor – ways in which temperament or mindset biases how one moves. Indeed, Laban noted that performers "can have different attitudes depending on temperament" toward Space, Weight, Time, and Flow [5]. Movement Pattern Analysis pioneer Warren Lamb further demonstrated that people's decision-making processes correlate with movement patterns: he "broke down the decision-making process into three stages – Attending, Intending and Committing" [6] (where "Committing" corresponds to what we term *Deciding*). Lamb's studies showed that "people's dynamic movement and non-verbal behaviours signalled core motivations and cognitive processes behind actions and decisions" [7]. In other words, how one *attends* to the world, formulates *intentions*, and *decides* (commits) is reflected in the qualitative aspects of their movement. The cognitive spectrums of our model draw from these insights, adding *Adapting* as a fourth dimension to account for how freely one adjusts or controls movement (analogous to Laban's Flow, which Lamb's three-stage decision model did not explicitly include).

Each cognitive spectrum spans between two poles (e.g. Deciding: tentative/light vs. forceful/strong), giving a **binary** in terms of presence/absence of a quality in a given moment. This does not mean the qualities are literally "on/off" switches – in reality they are continuous – but for analytical modeling we consider the *dominant* choice on each spectrum in a given action: e.g. is the movement primarily quick or sustained? Direct or flexible? Strong or light? Bound or free? Laban's theory identified these as *Effort Elements* and noted that each Effort factor's poles often have an antagonistic relationship (one tends to "indulge" in one end or "fight" against it) [8]. The cognitive-effort model uses these binary classifications (high vs. low in each quality) as building blocks to categorize movements and infer underlying mental state.

Inner Attitudes and States

The term **inner attitudes** in this context refers to configurations of these cognitive qualities that reflect a person's internal state of mind or mood. In Laban's framework, certain combinations of Effort qualities (particularly combinations of two factors) are called *States*, which often correspond to mood-like or cognitive states [9]. For example, the combination of Space and Time (Attending + Intending, without Weight or Flow) is called the **Awake** state – characterized by alertness and clarity (fitting, as one is focused in space and urgent in time) [10]. The combination of Weight and Flow (Deciding + Adapting, without Space or Time) is the **Dreamlike** state – a more internal, indulgent attitude (strong inner feeling + fluid continuity) [10]. These states (there are six in Laban's taxonomy, e.g. **Stabile** = Space+Weight, **Mobile/Labile** = Time+Flow, etc. [11]) represent inner attitudes where two cognitive-effort qualities are present while the others recede. They link to distinct psychological moods or cognitive dispositions [12].

In the cognitive-effort cube model, inner attitudes can be understood as the internal "setting" of one or more cognitive spectrums that underpins how an action is prepared. For instance, a person might have an inner attitude of **Visionary (Space+Time+Flow)** corresponding to Laban's Vision Drive (more on drives below) – this could manifest as a creative, imaginative mindset, where Intending, Attending, and Adapting are all engaged but Deciding (Weight) is held back (less emphasis on force). Another person might adopt an inner attitude of **Passionate (Weight+Time+Flow)** – a state of intense commitment and urgency (Deciding, Intending present) with emotional flow, but without clear spatial focus (Attending absent) [13]. These nuanced configurations help explain the *qualitative feel* behind movement: they are the inner context (motivation, feeling, decision-bias) that gives rise to observable effort combinations. The **inner attitudes** term emphasizes that we are considering the psychological side (cognitive/emotional predisposition), which the model then maps to *external* movement qualities. In summary, inner attitudes are the mindset settings (selection of cognitive spectrums activated) that a person carries, which in combination lead to particular movement dynamics or *drives*.

Externalized Drives: Doing, Spell, Passion, Vision

When three of the four cognitive spectrums are strongly present in an action, they combine to form what we call **externalized drives** – overarching patterns of action that are outwardly observable. These correspond directly to Laban's Effort *Drives*, which are combinations of three Effort factors (with the fourth factor latent or absent) [14]. There are four such drives in Laban's theory, each providing a broad characterization of the action's dynamic **intent**:

- **Doing Drive** – characterized by Deciding, Attending, and Intending (Weight, Space, Time) present, with Adapting (Flow) minimized. In Laban's terms this is the **Action Drive**, involving Space, Weight, Time and *no Flow* [13]. We label it "Doing" to emphasize its outward, goal-directed nature – it's about *what* you are doing, accomplishing a task with efficiency. The absence of Flow (Adapting) means movements in this drive are typically more discrete and task-focused (not continuously modulated by emotional flow). The **Doing/Action drive** yields the most clear-cut, functional actions. For example, a person in "doing mode" might move in a straightforward, no-nonsense way – exerting effort with clarity, force, and timeliness, uncolored by spontaneous flourishes. Laban considered the Action Drive as the foundation of the effort system, giving rise to the eight basic *Action Efforts* [15] (discussed in the next section).

- **Passion Drive** – characterized by Deciding, Intending, and Adapting (Weight, Time, Flow) present, with Attending (Space) absent [13]. This drive is dominated by strong weight and emotional flow in time, without a clear spatial focus – hence associated with *passionate* expression. We call it **Passion** drive (Laban's term as well) because it externalizes inner intensity and feeling. Movements in Passion drive have force (strength), urgent or sustained timing, and fluidity, but they may lack directionality or spatial precision. It's as if the person is swept by inner passion, moving powerfully and with feeling, but not necessarily aiming at a specific external target (space factor is missing). This could be seen in, say, an impassioned or emotionally expressive dance where the person pours energy and emotion into movement (Weight+Flow), with dramatic timing, but the movement pathways are more about inner expression than precision in space.

- **Vision Drive** – characterized by Attending, Intending, and Adapting (Space, Time, Flow) present, with Deciding (Weight) absent [16]. This drive emphasizes seeing possibilities and idea-driven movement – hence the term **Vision**. It has the qualities of quick/sustained time and direct/indirect space coupled with free/bound flow, but without the weight factor (so little force or impact). Laban noted the Vision Drive (Space, Time, Flow) tends to have a more observational or imaginative quality (one might also call it the *Dream* or *Idea* drive) [13]. Movements in Vision drive might be light and free, with varying tempo and exploratory spatial patterns – like someone "envisioning" or ideating through movement. The absence of weight means these actions don't assert force; they appear more exploratory or communicative (imagine gesturing while brainstorming – lots of shaping and flowing in space and time, but not much forceful contact).

- **Spell Drive** – characterized by Deciding, Attending, and Adapting (Weight, Space, Flow) present, with Intending (Time) absent [16]. "Spell" suggests a captivating or steady presence – and indeed this drive combines strong weight (commitment) with spatial focus and emotional flow, but without urgency of time. The **Spell drive** has a indulging, lingering quality – one might say it "casts a spell" through sustained presence. Movements in Spell drive are direct or indirect in space and can be powerful (weight) and fluid (flow), but they are *sustained* rather than sudden, as Time effort is missing. This can be seen in, for example, a very controlled, continuous, and weighty movement sequence that mesmerizes with its steady intensity (no quick surprises in timing). The person appears absorbed in the moment, fully committed (deciding) and absorbed (attending) with continuous flow, but *not* pushed by time pressure.

These four drives are "externalized" in the sense that they describe the overall complexion of a movement sequence that an outside observer can notice. Each is essentially the expression of three cognitive-attitudinal qualities working together. Notably, Laban's drives have been associated with different psychological intents: *Action/Doing* for practical goal-directed activity, *Passion* for emotional expression, *Vision* for imaginative or analytical engagement, and *Spell* for meditative or controlled sustained action [17] [12]. By naming them as Doing, Passion, Vision, Spell, we highlight the link between the mover's inner focus and the outer dynamic pattern. They effectively bridge inner attitude and outward movement: e.g. a Passion drive movement reveals that the person's inner attitude prioritizes commitment (Weight) and flow of feeling, while a Vision drive movement reveals an inner attitude of curious exploration (Space) and adaptability, without strong will (no Weight). These drives also illustrate how the presence or absence of one spectrum shifts the whole character of the action.

Inner Attitudes vs. Externalized Drives: It's worth clarifying that "inner attitudes" (as defined earlier) encompass any subset of qualities affecting mindset, whereas "externalized drives" specifically refer to the *overt pattern* when three qualities are present and shape the movement. One could say the drives are what happen when inner attitudes (cognitive spectrums) reach a certain critical combination that yields a distinct observable motif. The drives sit one level above the fine-grained effort elements – they are like the *modes* of action the person can enter. Next, we delve into the even more specific level: the eight **working actions** that form the corners of the cube.

Cube Model of Working Actions (Binary Combinations)

When we consider the binary presence/absence of *three* spectrums at a time (as in the Doing/Action drive where Flow/Adapting is absent), we get a set of **eight possible combinations** – analogous to the eight corners of a cube in a 3-dimensional space. This is the essence of the **cube model of working actions**. Each axis of the cube corresponds to one cognitive spectrum (and its associated effort quality), and each axis has two poles (e.g. Intending: Quick vs Sustained; Attending: Direct vs Flexible; Deciding: Strong vs Light). By selecting one pole on each of the three axes, we determine one corner of the cube – a unique trio of qualities. These trios are precisely Laban's famous **Eight Action Efforts** (also called the eight Basic Actions), which he named descriptively as: **Punch, Press, Dab, Flick, Slash, Wring, Glide,** and **Float** [15] .

To illustrate, consider the Doing/Action drive (no Flow): the three relevant spectrums are Intending (Time), Attending (Space), Deciding (Weight). Each can be either in its high-energy or low-energy state (presence of one polarity or the other): - Intending: Quick or Sustained, - Attending: Direct or Flexible (Indirect), - Deciding: Strong or Light.

All possible $2 \times 2 \times 2 = 8$ combinations of these yield the eight working actions: - **Punch** – *Quick* + *Direct* + *Strong*: An action that is sudden in timing, sharply focused in space, and forceful in weight. This is an attacking, definitive motion (like a literal punch) [18] . - **Press** – *Sustained* + *Direct* + *Strong*: Gradual in timing, straight in direction, and strong in force. The image is of *pressing* firmly but steadily – controlled power. - **Flick** – *Quick* + *Flexible* + *Light*: A sudden, indirect, and light movement. For example, a quick playful flick of the hand – it's brisk, with a flexible trajectory, and not forceful [18] . - **Slash** – *Quick* + *Flexible* + *Strong*: A sudden and strong movement with an indirection in its path – like a slashing motion, powerful but not carefully directed. - **Dab** – *Quick* + *Direct* + *Light*: A short, fast, precise yet light touch – imagine *dabbing* a finger quickly at a point. It's controlled in aim and timing but gentle in force. - **Glide** – *Sustained* + *Direct* + *Light*: Smooth, sustained, direct, and light – gliding suggests an effortless, continuous, and focused motion (gentle and unhurried). - **Wring** – *Sustained* + *Flexible* + *Strong*: Think of wringing out a cloth – it is sustained (slow), uses strong force, and has an indirect twisting path. Wringing motions are intense and bound in effort. - **Float** – *Sustained* + *Flexible* + *Light*: A light, leisurely, and indirect movement, as if *floating*. It has no urgency, no strong force, and no single focus – e.g. a leaf floating down unpredictably [18] .

These names are vivid metaphors Laban chose; in practice any movement or "working action" that has the corresponding qualities could be classified as that type (even if you're not literally punching or gliding). The cube model provides a mental (and visual) map of how these eight actions relate: each is opposite another on the cube, etc. The **edges** of the cube represent changing one quality (for instance, moving from *Punch* to *Press* means changing Quick to Sustained while keeping Direct and Strong). The cube structure thus helps us see relationships and transitions between action patterns.

The term **working actions** highlights that these are fundamental action patterns used in work or daily functional movement, not just abstract qualities. They are building blocks of expressive movement and have been used in acting training to quickly shift physical demeanor [19] . Psychologically, one can think of them as embodying distinct "attitudes in action". For example, *Punch* carries an attitude of assertive decisiveness (all three high-intensity qualities present), whereas *Float* carries an attitude of carefree openness (all three intensity qualities low or indulging). In Laban's analysis, each of the eight has a distinct *effort rhythm* and can even be associated with different emotions or intentions in context (Punch might feel aggressive or determined; Float might feel relaxed or whimsical, etc.). Research in movement analysis often considers these eight action types as basic descriptors for movement quality that observers can identify.

Importantly for our model, each working action is the external **result** of a particular combination of cognitive qualities. If we detect that someone's movement is, say, Quick, Direct, and Strong, we infer that the person's cognitive state at that moment likely involved a Deciding attitude (commitment to force), focused Attending (direct attention), and urgent Intending (time-pressure) – in other words, a mindset geared toward a very **urgent, focused decision**. If instead we observe a movement that is Sustained, Flexible, Light (Float), we infer an entirely different cognitive stance: no strong commitment (light weight), no urgency (sustained time), and an open, multi-focused attention (indirect space) – possibly a *contemplative or exploratory* mindset. In this way the cube of actions serves as a translation key between *observables* (movement qualities) and *unobservables* (cognitive intent/attitude).

It's worth noting that while the eight actions were historically defined without the Flow factor, one can extend the cube concept by including Flow/Adapting as a fourth dimension (leading to 16 combinations if we include Free vs Bound). In practice, however, the eight basic actions assume a neutral middle in Flow (neither extremely bound nor free) [20]. The transformation drives (Spell, Vision, Passion) discussed earlier come into play when Flow is added in, creating more nuanced variations (for instance, a *Press* action done in a Free flow vs a Bound flow will have a different feeling, aligning with Spell vs Action drive contexts). For foundational understanding, the cube of eight is usually depicted with Flow held constant (not defining it), which is why we emphasize those three spectrums.

In summary, the cognitive-effort cube model encapsulates a hierarchy: *Effort Elements* (binary poles like Quick/Sustained) combine into *Working Actions* (specific combos of three qualities, the cube corners), and these in turn cluster under *Drives* (groupings of actions sharing the same absent quality). This hierarchy moves from fine-grain to broader patterns, paralleling how inner cognitive attitudes manifest in degrees: momentary impulses (elements), basic action patterns, and overall drive modes. The validity of this structure is supported by both experiential practice (the fact that observers and performers reliably identify these qualities [19]) and empirical research. For instance, studies have successfully *quantified* these effort qualities in movement and used them for classification: one study notes that the eight effort elements (Direct/Indirect, Quick/Sustained, Strong/Light, Free/Bound) "can be related to motion features such as velocity and acceleration" [21]. This leads us to the bridge toward computation – how we detect and analyze these qualities in data.

Modeling Movement with Rhythm and Frequency

One of the central ideas for bridging to computational analysis is that many effort qualities – especially those related to Time and Flow – have clear signatures in the *temporal rhythm* of movement. Human **gait** (walking patterns) is an excellent example to illustrate this. Gait is inherently rhythmic: as we walk, our limbs swing in periodic cycles. This periodic nature means we can use **frequency** (how fast the cycles repeat) and **rhythmic patterning** as measurable proxies for certain cognitive intentions.

Consider the Intending (Time) spectrum: a person walking with a *quick* time effort will have a faster gait cadence (more steps per minute, i.e., higher step frequency) than someone walking with a *sustained* time effort (who will take slower, more drawn-out steps). Frequency here directly reflects the urgency of intention – running or fast walking corresponds to a high-frequency periodic motion, whereas strolling corresponds to a low-frequency motion. Similarly, the Flow (Adapting) spectrum relates to how continuous and smooth the gait rhythm is. A *bound* flow gait might have noticeable pauses or stiffness (discontinuities in the smooth rhythm), whereas a *free* flow gait will be very even and unbroken (the motion flows at a steady beat). Space (Attending) can also manifest in rhythm if we consider directional changes: a *direct* approach to walking (like walking straight toward a goal) will have a very regular, consistent rhythm (and a consistent heading), whereas an *indirect/flexible* approach (meandering, looking around) might lead to irregular timing – perhaps slowing to turn or accelerating sporadically.

Weight (Deciding) influences the dynamics of each step: a *strong* weight effort might produce an impulsive, emphatic rhythm (think of heavy stomping – which often has a pronounced impact at each step and possibly shorter contact times), whereas a *light* effort produces a softer rhythm (lighter footfalls, possibly more time in foot contact, yielding a slightly different temporal profile).

To formalize these intuitions, we can turn gait data into the frequency domain and other temporal descriptors. Modern tools like **MediaPipe Pose** (BlazePose model) can capture a person's 3D skeletal motion from video, yielding coordinates of key joints over time [22]. MediaPipe, for example, provides 33 landmark points (including major joints like ankles, knees, hips, etc.) in real time [22]. Similarly, research models like **MotioNet** reconstruct a temporally coherent 3D skeleton from monocular video input [23], providing sequences of joint positions. Once we have the skeletal wireframe data – essentially time-series signals for joint angles or positions – we can analyze their **rhythm**.

One approach is to perform a **Fourier Transform** on the time-series of joint motion to find dominant frequencies. Because gait is approximately periodic, the Fourier spectrum will typically show a peak at the fundamental step frequency (for walking, often around 1–2 Hz for normal walking speeds, higher for running) [24]. Research confirms that "gait sequences inherently have obvious periodicity" and that frequency-domain analysis is effective in capturing "the rhythmic and cyclical nature of human gait patterns" [24]. By extracting the dominant frequency and perhaps a few harmonics, we get a compact representation of the gait's tempo and regularity. A higher dominant frequency indicates a quicker pace (Intending present as Quick), whereas a lower frequency indicates a sustained, lingering pace [24]. If we also examine the energy distribution: a very *even* gait (consistent rhythm) will have a sharp, strong fundamental frequency and low variability, whereas a gait with more variability or irregular timing (perhaps due to adapting to the environment or pausing, etc.) will have a more spread-out frequency spectrum or multiple frequency components.

We can also derive features in the time domain that relate to rhythm and effort: for example, the stride interval (time between steps) and its variance, the smoothness of velocity profiles, etc. A *bound* (controlled) gait might have relatively fixed stride intervals (low variability) but possibly higher-frequency content in acceleration (due to stiff regulation causing subtle oscillations), whereas a *free* gait might allow slight natural variance but overall smoother acceleration profiles. Likewise, a *strong* weight effort might be inferred from higher impact peaks – if we had ground reaction force it'd be obvious, but even from kinematics, a strong effort may correspond to faster deceleration of the foot at heel strike (a sharper change in velocity, which shows up as higher-frequency components or higher peak acceleration). A *light* effort yields softer landings (lower peaks, more sinusoidal movement). In fact, prior work has used features like joint velocity and acceleration magnitudes to predict Laban effort qualities [21]. For example, one study created classifiers for Light vs Strong effort by looking at acceleration patterns of limbs [25] [26]. They found such motion features mapped well to the qualitative labels provided by human experts [26].

In summary, by analyzing **rhythm and frequency**, we translate the qualitative language of movement (sustained vs sudden, etc.) into quantitative signals. Rhythm is essentially the *fingerprint* of Intending (Time) and, to an extent, Flow (Adapting), while certain aspects of the waveform (like amplitude and shape) relate to Weight (Deciding) and Space (Attending). This gives us proxies for cognitive intention: e.g., *high step frequency = Quick intention*, *variable rhythm = more Adaptable/Free flow*, *consistent straight path = Direct attention*, *erratic path or hesitation = Indirect attention*, *high acceleration peaks = Strong force*, *smooth gentle kinematics = Light effort*. Each of these can be measured or computed from movement data.

From Gait Data to Frequency Profiles (Computational Parsing)

How do we go from a 3D skeletal time-series to the kind of frequency-based descriptors discussed? Let's outline the process step by step (and then demonstrate with a bit of code):

1. **Capture or Input Movement Data:** Using a tool like MediaPipe or MotioNet, we obtain the 3D coordinates of key joints over time for the movement of interest (say, a person walking a few steps). For example, MediaPipe's BlazePose model provides 33 landmarks per frame covering the full body [22]. Each landmark gives (x,y,z) in a normalized coordinate system. A gait recording at 30 frames per second for 10 seconds will yield 300 data points per joint.

2. **Preprocess and choose signals:** We typically focus on signals that reveal periodic motion. For gait, the vertical position of the ankle or the angle of the knee might be good choices, as they oscillate each step. We might also look at the trajectory of the person's center of mass or their footfall timing extracted from when feet contact the ground. For simplicity, one could use the y-coordinate (vertical) of the left ankle across frames as a representative periodic signal of gait (it will go up and down with each step). If analyzing other kinds of movement, one might choose the most varying joint or a composite signal.

3. **Transform to Frequency Domain:** Apply a Fast Fourier Transform (FFT) to this time-series. This yields a set of frequency components and their magnitudes (a frequency spectrum). The highest magnitude peak in the spectrum corresponds to the dominant periodic frequency in the motion [27]. For walking, suppose we find a dominant frequency of 2.0 Hz – that implies roughly 2 cycles per second, meaning the person is taking ~120 steps per minute (since one gait cycle is often one full stride, or two steps, depending on definition). If another person's gait yields 0.8 Hz dominant frequency, that's only ~48 steps per minute, indicating a very slow, sustained walk. Thus we immediately see a quantitative handle on Quick vs Sustained effort. Additionally, the **spectral energy distribution** (how much energy is in the fundamental vs harmonics) can tell us about movement consistency: a very regular motion (like a metronomic walk) will have most energy at the fundamental and maybe second harmonic, whereas irregularities or slight changes produce more spread (energy at additional frequencies, noise floor, etc.). A bound, carefully controlled walk might actually introduce more *high-frequency tremors* (due to muscle co-contraction) than a free relaxed walk, which might appear smoother (more energy concentrated at the main frequency and low harmonics). These are hypotheses that can be tested by examining the spectra.

4. **Extract Time-Domain Features:** In parallel to FFT, we can compute time-based features: for example, detect peaks in the ankle y-position signal to mark each step, then compute the intervals between peaks (step durations). From that we get average step duration and its standard deviation. The average gives another measure of frequency; the variability gives an indication of how much the timing adapts (which could be linked to Flow/Adapting quality – more variance might suggest flexibility or instability, depending on context).

5. **Compute Directional and Acceleration Metrics:** To address Space (Attending) and Weight (Deciding) qualities, we extend beyond pure frequency. For Space/Directness, one could compute the trajectory of the person's center or heading over ground and see how much it deviates. A simple measure is the line deviation: how far does the path wander from a straight line? A high deviation or a lot of directional change (perhaps measured as variance in the direction angle per step) would correlate with Indirect (flexible attention) movement; minimal deviation (very straight path) correlates with Direct focus. This can even be treated in a frequency way –

frequent changes in heading indicate an indirect/flexible approach (the person is turning or adjusting often, introducing a higher-frequency component in the orientation signal). For Weight/force, as discussed, one might calculate the peak vertical acceleration of the center of mass or foot at each step. High peaks (and short contact durations) imply a strong, forceful style (Deciding present), whereas lower peaks (and longer, softer contacts) imply a light style. These could be captured via time-series of acceleration (e.g., use finite differences on the velocity of a joint) and analyzing their magnitude distribution or even their frequency content (a strong impact can introduce high-frequency shock components in the acceleration signal). Indeed, an “Effort classification” study found that features like the velocity and acceleration of ankles, hips, etc., fed into a machine learning model, were able to classify Light vs Strong and other effort dimensions with reasonable accuracy [28] [26].

6. **Combine Qualities to Identify Actions:** Once we have quantitative indicators for each of the three primary qualities (and possibly Flow as well), we can classify each segment of movement. For example, if the analysis of a gait segment yields: dominant frequency = 2.2 Hz (Quick), path deviation = low (Direct), accel peaks = high (Strong), then we classify that segment’s effort as **Quick+Direct+Strong**, which corresponds to the working action **Punch**. If another segment yields: freq = 0.7 Hz (Sustained), path deviation = high (Indirect), accel peaks = low (Light), that would classify as **Float** (Sustained+Flexible+Light). By doing this frame-by-frame or over moving windows, we can even track how a person transitions between effort states.

Below is a brief illustrative Python code snippet demonstrating part of this process – taking a simulated joint motion, converting to a frequency profile, and then classifying the effort qualities and resultant working action:

```
import numpy as np

# Simulated vertical motion of a joint (e.g., ankle) during gait
fps = 30  # frames per second
t = np.linspace(0, 5, 5*fps, endpoint=False)  # 5 seconds timeline
# Simulate a periodic gait signal: e.g., 2 Hz base frequency (quick steps)
with some harmonic content
y = 0.1 * np.sin(2 * np.pi * 2 * t)            # base 2 Hz oscillation
(vertical movement)
y += 0.02 * np.sin(2 * np.pi * 4 * t)          # add a second harmonic at 4
Hz
y += 0.01 * np.random.randn(len(t))            # add slight noise

# Compute frequency spectrum
Y = np.fft.rfft(y)
freqs = np.fft.rfftfreq(len(t), d=1.0/fps)
dom_freq = freqs[np.argmax(np.abs(Y))]         # dominant frequency in Hz

# Classify Intending (Time Effort) based on frequency threshold (e.g., >1.5
Hz is Quick)
time_effort = "Quick" if dom_freq > 1.5 else "Sustained"

# (In practice, we'd calculate analogous features for Space and Weight
efforts. Here we assume results:)
space_effort = "Direct"    # e.g., low path deviation observed
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```
weight_effort = "Strong"   # e.g., high acceleration peaks observed

# Determine the working action from the combination of qualities
action = None
if (time_effort, space_effort, weight_effort) == ("Quick", "Direct",
"Strong"):
    action = "Punch (Quick, Direct, Strong)"
elif (time_effort, space_effort, weight_effort) == ("Sustained", "Flexible",
"Light"):
    action = "Float (Sustained, Flexible, Light)"
# (and so on for other combinations...)

print(f"Dominant frequency = {dom_freq:.2f} Hz -> Time Effort:
{time_effort}")
print(f"Combined Effort qualities: {time_effort}, {space_effort},
{weight_effort} -> Working Action: {action}")
```

For this simulated example, the output might be:

```
Dominant frequency = 2.00 Hz -> Time Effort: Quick
Combined Effort qualities: Quick, Direct, Strong -> Working Action: Punch
(Quick, Direct, Strong)
```

This toy code shows the concept: using an FFT we extracted a dominant frequency of ~2 Hz, classified that as "Quick" time effort, assumed some directness and strength measures, and then identified the action as Punch. A real implementation would derive `space_effort` and `weight_effort` from actual data analyses: e.g., `space_effort = "Direct"` if the angular deviation of travel < some threshold, or if a Fourier analysis of the heading shows low power at turning frequencies; `weight_effort = "Strong"` if peak acceleration > threshold or if spectral energy in high-frequency band (indicative of impact transients) is high, etc. Machine learning could be employed to find optimal thresholds or more complex decision boundaries, possibly using a training set of movement labeled by experts. In fact, researchers have built classifiers in this manner: one pilot study trained an AI model to recognize Laban effort qualities from video, achieving good accuracy on binary classifications like Light vs Strong by leveraging features such as velocities and accelerations of key joints [26] [28].

It is also possible to classify the higher-level drives (Doing, Passion, etc.) by detecting which quality is absent. For instance, if we detect an Action like Punch, Dab, Press or any of those eight with no flow modulation, we know the person is in the **Doing (Action) Drive** (all three effort factors focused, flow is minimal). If we detect a movement that has strong flow and weight and time but lacking spatial focus, it suggests the **Passion Drive**, and so on [13]. In practice, classifying drives might involve looking at segments of movement and seeing if one factor remains neutral or if flow is present (perhaps measuring movement continuity can indicate presence of flow: very constant velocity might mean free flow, frequent starts/stops might mean bound flow).

From Theory to Machine Learning: A Foundational Bridge

The cognitive-effort cube model outlined here serves as a bridge between **movement psychology theory** and **applied computational analysis**. It provides a structured language to move from qualitative observation to quantitative features. By formalizing cognitive spectrums and effort qualities, we gain interpretable features that can feed into machine learning models for motion analysis. Instead of treating human motion as an opaque sequence of coordinate data, the model guides us to derive features like "dominant frequency (Hz) of motion = 2 Hz" or "path deviation = 0.5 m" which have semantic meaning (quick tempo, indirect path) and psychological inference (urgent intention, flexible attention). This is invaluable for AI systems aimed at understanding or classifying movement in a human-like way.

In the context of an AI movement psychology project, this model becomes the **"source of truth" framework** – new data can be labeled in terms of these cognitively-meaningful categories, and models can be trained to predict them. The eight working actions give a concrete classification schema for supervised learning (with expansion to drives or states for higher-level descriptions). Indeed, prior work in affective computing and human-computer interaction has used Laban's effort qualities for emotion recognition from body language, precisely because they encapsulate *how* something is done rather than just *what* is done [29]. Our model extends that idea with a cognitive interpretation, suggesting that an AI that recognizes these qualities could in effect be reading a person's cognitive-emotional state from their movements.

One of the strengths of using a model grounded in Laban's theory is that it has **face validity** and a rich heritage in the performing arts, therapy, and ergonomics. It has been tested in practice: actors train to adopt the eight effort actions to convey emotions [19], and movement analysts profile leaders' decision-making styles using Lamb's movement pattern analysis [7]. By connecting these proven qualitative frameworks to computational methods (e.g. using pose estimation, signal processing, and machine learning), we ensure that our AI systems are not just crunching numbers, but are anchored to meaningful human categories.

Furthermore, this model facilitates interpretability in machine learning. Instead of a black-box gesture classifier that outputs "class 7" without explanation, a system built on this model could output "the person is exhibiting a sustained, indirect, light movement (Float action), indicative of a relaxed exploratory state." This interpretability is crucial for applications like healthcare (monitoring Parkinson's gait for changes in movement qualities), security (identifying aggressive intent vs distracted wandering from surveillance footage), human-robot interaction (robots adjusting their responses based on the detected state of a human partner's movements), and creative arts (tools that respond to dancers' movement qualities in real-time).

Finally, the cognitive-effort model invites a two-way enrichment between psychology and AI. As we implement and test it, we may discover patterns – for example, perhaps certain combinations of qualities are predictive of cognitive load or emotions in ways not initially theorized. We might find that "bound flow + sustained time" correlates with certain stress states in gait, adding new insight to psychology. Conversely, the theory guides the AI to look for features that matter, which is especially valuable in an era of big data where countless features could be extracted – it narrows the search space to those dimensions that have known relevance. This synergy embodies the idea of *movement psychology-informed AI*: using human theoretical understanding to shape computational models, which in turn can handle scale and provide objective validation or discovery.

In conclusion, the cognitive-effort cube model establishes a foundational theory that unites qualitative movement analysis with quantitative computation. By defining clear axes between mind and motion – Deciding/Weight, Attending/Space, Intending/Time, Adapting/Flow – it allows us to dissect and describe movement in cognitive terms. The cube of working actions provides a pragmatic taxonomy for coding movement data, and the extension to rhythmic and frequency analysis shows a path to implementation. This creates a framework for future research in the **AI Movement Psychology** project: researchers can expand on each aspect (e.g., refining algorithms to detect "directness" or "strength" from sensor data, exploring gait frequency under different cognitive tasks, etc.), confident that these aspects are grounded in a rich theoretical context. As we develop machine learning models on top of this framework, we move closer to AI systems that not only **see** how people move, but also **understand** the psychological significance of those movements – effectively bridging the gap from expressive motion to mind.

Sources:

- Laban movement analysis theory – Effort factors and their polarities [1] [8]; Effort drives and action combinations [17] [15].
- Warren Lamb's movement research linking Attending, Intending, Committing (Deciding) to decision-making processes [7].
- Research on movement quality recognition: mapping Laban effort elements to motion features like velocity/acceleration [21].
- Gait analysis using frequency domain: gait's inherent periodicity and capturing of rhythmic patterns via Fourier analysis [24].
- MediaPipe and MotioNet for skeletal data extraction: e.g. BlazePose model (33 landmarks) [22]; MotioNet reconstructing 3D skeleton from video [23].
- Application of effort detection in ML: pilot study using joint velocities to classify LMA qualities [28].
- Psychological interpretation of effort states and drives [12].

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